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**Are Predictable Improvements in TFP Contractionary or
Expansionary: Implications from Sectoral TFP?***

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Abstract

We document in the US data: (1) The dominant predictable component of investment-sector TFP is its long-run movements, and a favorable shock to predictable changes in investment-sector TFP induces a broad economic boom that leads actual increases in investment-sector TFP by almost two years, and (2) predictable changes in consumption-sector TFP occur mainly at short forecast horizons, and a favorable shock to such predictable changes leads to immediate reductions in hours worked, investment, and output as well as an immediate rise in consumption-sector TFP. We argue that these documented differences in the responses to shocks to predictable sectoral TFP changes can reconcile the seemingly contradictory findings in Beaudry and Portier (2006) and Barsky and Sims (2011), whose analyses are based on aggregate TFP measures. In addition, we find that shocks to predictable changes in investment-sector TFP account for 50% of business cycle fluctuations in consumption, hours, investment, and output, while shocks to predictable changes in consumption-sector TFP explain only a small fraction of business cycle fluctuations of these aggregate variables.

JEL codes: E1, E3

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1 Introduction

In structural vector autoregression (SVAR) models, Beaudry and Portier (2006) document that long-run improvements in aggregate total factor productivity (TFP)¹ are preceded by a broad boom in the economy in which consumption, investment, hours worked, and stock prices all increase. One potential explanation of their finding is that agents have advanced information (news) about future technological opportunities when they make current economic decisions.² Good news about future technology growth increases agents' expectations about future fundamentals, and therefore induces an economic boom even before the actual increase in technology. Beaudry and Portier find that these predictable (or anticipated) movements in TFP are important in explaining US business cycle fluctuations and call for developing business cycle models that can replicate these findings.

In another SVAR study, Barsky and Sims (2011) find that news (anticipated) shocks to TFP do not induce broad-based economic comovements. In particular, they document in the US data that a favorable news shock to TFP leads to increases in consumption and stock prices, but declines in hours, investment, and output on impact; moreover, after impact, those aggregate variables track, rather than anticipate, predicted improvements in TFP.

In this paper, we reconcile these two seemingly contradictory findings by exploring the effect of predictable changes in sectoral TFP on US business cycle fluctuations. Recent empirical studies on news TFP shocks increasingly use the factor-utilization-adjusted aggregate TFP series that is first developed by Basu, Fernald, and Kimball (2006) and regularly updated by Fernald (2010) on his website.³ Besides adjusted aggregate TFP series, Fernald also provides two utilization-adjusted sectoral TFP series obtained by decomposing the aggregate TFP series into two sectoral TFP series: equipment investment and consumer durables sector TFP and consumption sector TFP (defined as business output less equipment investment and consumer durables).⁴ We refer to the first sectoral TFP series as investment-sector TFP and the second series as consumption-sector TFP.

We find that shocks to predictable changes in these two sectoral TFP affect aggregate economic variables very differently. Shocks to predictable changes in TFP are defined as shocks that have no immediate impact on TFP but explain future movements in TFP. Shocks to predictable changes in investment-sector TFP

¹“Aggregate” TFP means total factor productivity in all sectors of business output (for instance, including equipment investment and consumer nondurables). In what follows, we omit “aggregate” when it raises no confusion.

²An alternative explanation of their finding is that the increase in TFP following an economic boom reflects self-fulfilling beliefs that cause the economic boom. See Beaudry, Nam, and Wang (2011) for more discussions.

³See for example Barsky and Sims (2011), Kurmann and Otrok (2011), and Ben Zeev (2011).

⁴See Fernald (2010) for more details on his (non-adjusted and adjusted) aggregate and sectoral TFP series. Loosely speaking, the aggregate TFP series is a weighted sum of the investment- and consumption-sector TFP series, where the weight to the investment-sector TFP series is around 0.2.

are found important in driving long-run movements in investment-sector TFP, while shocks to predictable changes in consumption-sector TFP explain much of consumption-sector TFP at short forecast horizons. Shocks to predictable movements in investment-sector TFP are also found expansionary, while shocks to predictable movements in consumption-sector TFP are mainly contractionary. Such heterogeneity will likely confound analyses based on aggregate TFP measures, and it also accounts for seemingly contradictory findings in the literature regarding the effect of anticipated changes in aggregate TFP. We will discuss these results with more details after briefly describing the identification methods used in this paper.

We employ two variants of the maximum forecast error variance approach (Uhlig, 2003) in a VAR system to isolate shocks that are associated with predictable movements in (aggregate and sectoral) TFP: the first is the max share method introduced by Francis et al. (2005) and the second is the method proposed by Barsky and Sims (2011). Along with the restriction that such shocks have no immediate impact on TFP, the max share method identifies these shocks by maximizing their share of the forecast error variance (FEV) of TFP at a finite forecast horizon, while Barsky and Sims' method maximizes the sum of the shocks' shares of the FEV of TFP over all forecast horizons up to a finite truncation horizon. In other words, both the max share and Barsky and Sims' methods aim at isolating a shock that has no contemporaneous effect on TFP, but accounts for future movements in TFP. We refer to such a shock as a shock to predictable TFP.⁵

We want to emphasize two points about applying the max share and Barsky and Sims' methods to identify shocks to predictable changes in TFP and study their effects on aggregate economic variables. First, we can distinguish short-, medium-, and long-run anticipated changes in TFP and gauge their relative importance in driving aggregate economic variables by varying the value of the finite horizon parameter used in each of these two methods, in particular, the max share method. Second, Barsky and Sims' method is designed to capture the effects of both short- and long-run predictable changes in TFP, since it maximizes the sum of the FEV shares of TFP over all horizons up to a finite truncation horizon. When the truncation horizon is long (40 quarters as in Barsky and Sims (2011) for example), the summation of the FEV shares of TFP are affected by shocks to predictable TFP at both short and long forecast horizons. In contrast, the max share method focuses on the FEV share of TFP at a specific horizon. When the horizon is set to 40 quarters, the max share method is likely to exclusively pick up long-run predictable changes in TFP.

We first apply both methods to a VAR system of the US data with either investment-sector TFP or consumption-sector TFP as a measure of TFP. In particular, by varying the value of the finite horizon used in the max share method,⁶ we find that the important predictable component of investment-sector TFP is its

⁵We refrain from referring to the identified shocks as “news TFP shocks” because, as discussed in Beaudry, Nam, and Wang (2011), these shocks could reflect self-fulfilling beliefs, rather than advanced information about future technology.

⁶Barsky and Sims' method gives similar results.

long-run movements and that a favorable shock to predictable investment-sector TFP is expansionary, while by contrast, the predictable component of consumption-sector TFP is in its short-run movements and is mainly contractionary. More specifically, following a favorable shock to predictable investment-sector TFP, consumption, hours worked, investment, and output all increase before investment-sector TFP starts to increase in the eight quarters following the shock. In contrast, a favorable shock to predictable consumption-sector TFP leads to significant declines in hours, investment, and output on impact, no immediate change in consumption, and an immediate increase in consumption-sector TFP. In addition, the identified shock to predictable changes in investment-sector TFP is found to play an important role in driving US business cycle fluctuations. At business cycle frequencies, the shock usually explains about 50% of the FEVs of consumption, hours, investment, and output. However, the identified shock to predictable consumption-sector TFP usually accounts for less than 10% of the FEV of US output at business cycle frequencies.

When we turn to the system with aggregate TFP in place of sectoral TFP, the results from the max share and Barsky and Sims' methods differ when the finite horizon is set to 40 quarters.⁷ Under the max share method, the impulse responses of all variables to a favorable shock to predictable changes in aggregate TFP are very similar to those to a favorable shock to predictable changes in investment-sector TFP. However, under Barsky and Sims' method, the results show the mixed effects of shocks to predictable changes in two sectoral TFP series. In particular, the impulse responses of hours, investment, and output to a favorable shock to predictable changes in aggregate TFP over the first several horizons resemble the results using consumption-sector TFP. When we lengthen the truncation horizon in Barsky and Sims' method to 80 quarters, however, the results resemble the effects of shocks to predictable changes in investment-sector TFP. By design, Barsky and Sims' method treats both short- and long-run predictable components of TFP equally when identifying shocks to predictable changes in TFP. As a result, when the truncation horizon is set to 40 quarters, the identified shock to predictable aggregate TFP is likely to capture the effect of the predictable component of consumption-sector TFP as well as that of investment-sector TFP. When the truncation horizon is set to relatively longer ones (80 quarters for example), more weight is given to long-run dynamics of aggregate TFP. As a result, the identified shock is dominated by the long-run predictable component of investment-sector TFP.

Therefore, our results suggest that the seemingly contradictory findings in Beaudry and Portier (2006) and Barsky and Sims (2011) stem from the facts that: (1) the long-run restrictions method used in Beaudry and Portier focuses on the long-run predictable components of aggregate TFP, while the method proposed by Barsky and Sims considers both short- and long-run predictable components of TFP; (2) long-run predictable

⁷Barsky and Sims (2011) use the finite horizon of 40 quarters.

changes in aggregate TFP are driven by investment-sector TFP which is expansionary, while short-run predictable movements in aggregate TFP are affected by consumption-sector TFP which is mainly contractionary. Besides reconciling seemingly contradictory findings in Beaudry and Portier (2006) and Barsky and Sims (2011), our findings in this paper also create an interesting challenge to the literature. Why do shocks to predictable changes in consumption- and investment-sector TFP behave so differently, and why shocks to predictable changes in investment-sector TFP are much more important than shocks to predictable changes in consumption-sector TFP in driving business cycles? It would be interesting to study if the standard business cycle models can replicate these findings and we leave this for the future research.

The remainder of the paper is organized as follows. Section 2 briefly explains the max share and Barsky and Sims' methods to identify shocks to predictable changes in TFP and describes the data used in our empirical study. Section 3 presents our empirical results and Section 4 concludes.

2 Identification Strategies and Data

In this section, we first briefly introduce the max share and Barsky and Sims' methods to identify shocks to predictable TFP, and then describe the data used in our empirical study.⁸

Let us begin by considering the reduced-form moving-average representation of a VAR model:

$$Y_t = \sum_{h=0}^{\infty} B(h) u_{t-h}, \quad (1)$$

where Y_t is an $n \times 1$ vector of variables in levels and u_t is reduced-form innovations with the variance-covariance matrix Σ_u . Then, it is assumed that there is a linear mapping between reduced-form innovations u_t and economically meaningful structural shocks ϵ_t : $u_t = A_0 \epsilon_t$, where variances of structural shocks are normalized to be equal to one (i.e., $E[\epsilon_t \epsilon_t'] = I$) and the impact matrix A_0 satisfies $A_0 A_0' = \Sigma_u$. Alternatively, we can rewrite A_0 as follows: $A_0 = \tilde{A}_0 Q$, where \tilde{A}_0 is any arbitrary orthogonalization of Σ_u (e.g., Cholesky decomposition of Σ_u) and Q is an orthonormal matrix (i.e., $Q Q' = I$). Therefore, the identification of a particular structural shock of interest amounts to uniquely pinning down a column of the orthonormal matrix, that is, a unit vector denoted by q , by imposing identifying restrictions.

Without loss of generality, let TFP (either aggregate TFP or each sectoral TFP) be the first element of Y_t and let q denote the unit vector associated with a shock to predictable TFP (if such a shock exists). It is straightforward to show that the share of the forecast error variance (FEV) of TFP attributable to this shock at a finite horizon h , which is denoted by $\Omega_1(h)$, can be expressed as:

⁸See Beaudry, Nam, and Wang (2011) for details on these two methods.

$$\Omega_1(h) = q' \mathbf{F}(h) q, \quad (2)$$

where $\mathbf{F}(h)$ is an $n \times n$ positive-definite, symmetric matrix, which is a function of the first rows of $B(h)$ in equation (1) and \tilde{A}_0 . Under the the max share method introduced by Francis et al. (2005), we assume that there exists a predictable TFP shock that does not have an immediate effect on TFP (and possibly other variables),⁹ but becomes a dominant force of driving TFP at a specific finite horizon h . Then, we can identify such a shock by solving the following maximization problem for a given h :

$$q^* = \arg \max_q \Omega_1(h), \quad s.t. \quad (1) \quad q'q = 1; \quad (2) \quad R(0)q = 0, \quad (3)$$

where $R(0)q$ represents the impact impulse responses of TFP and other variables to the shock and $R(0)$ is constructed by taking and stacking the rows of \tilde{A}_0 that correspond to TFP and other variables on which the identified shock has no immediate impact. So the second constraint $R(0)q = 0$ imposes the zero restrictions that the impact responses of TFP and other variables to the shock are zero. Under the method proposed by Barsky and Sims (2011), predictable (news) TFP shocks are identified by solving the following maximization problem:

$$q^* = \arg \max_q \sum_{h=0}^H \Omega_1(h), \quad s.t. \quad (1) \quad q'q = 1; \quad (2) \quad R(0)q = 0, \quad (4)$$

where $\sum_{h=0}^H \Omega_1(h)$ is the sum of the shares of the FEV of TFP attributable to the predictable TFP shock over all forecast horizons up to a finite truncation horizon H .

In our empirical study, we use quarterly US data from the sample period 1955Q1 to 2010Q4. The starting and ending dates of our sample are dictated by the availability of the data.¹⁰ Our dataset contains the following variables: aggregate TFP, two sectoral TFP as components of aggregate TFP, the relative price of investment to consumption, stock prices, consumption, investment, output, hours worked, and the real interest rate.

Our measures of aggregate TFP, investment-sector TFP, and consumption-sector TFP are the factor-utilization-adjusted TFP series for all business output, TFP series for equipment investment and consumer durables, and TFP series for business output less equipment investment and consumer durables, respectively.

⁹In our empirical study, we consider a VAR system with both aggregate and sectoral TFP. In this case, we might identify the predictable aggregate TFP shock as a shock that maximizes its contribution to the FEV of aggregate TFP and has no immediate impact on sectoral TFP as well as aggregate TFP. That is, we impose the zero restrictions on impact responses of three variables: aggregate TFP and two sectoral TFP series.

¹⁰The federal funds rate that is used to calculate the real interest rate starts in 1955Q1, and the factor-utilization-adjusted TFP series end in 2010Q4.

These three TFP series are obtained from John Fernald’s website. Our measure of the relative price of investment is the inverse of the series of the relative price of investment to consumption, which is used to calculate above-mentioned sectoral TFP series and also obtained from Fernald’s website.¹¹ Our stock prices measure is the end-of-period Standard and Poor’s 500 composite index divided by the CPI of all items for all urban consumers. S&P 500 index and CPI series are obtained from the *Wall Street Journal* and the Bureau of Labor Statistics (BLS), respectively. Consumption is measured by real consumption expenditures on nondurable goods and services from the Bureau of Economic Analysis (BEA). Investment is measured by real gross private domestic investment from the BEA. Output and hours worked are measured by real output and hours of all persons in the non-farm business sector, respectively, which are obtained from the BLS. These five variables (stock price, consumption, investment, output, and hours worked) are transformed into per capita terms by dividing each of them by the civilian noninstitutional population of 16 years and over from the BLS. The real interest rate is the effective federal funds rate from the Federal Reserve Board minus the inflation rate which is measured by the annualized quarterly CPI growth rate.

3 Empirical Results

This section reports our empirical results, focusing on point estimates of impulse responses and forecast error variance shares of variables.¹² Our benchmark VAR model includes eight variables: a measure of TFP (aggregate or sectoral TFP), stock prices, consumption, the real interest rate, hours worked, investment, output, and the relative price of investment.¹³ All variables enter the VAR system in levels, and a constant and four lags are included.

We first examine how the value of the finite horizon parameter used in the max share and Barsky and Sims’ method affects the identification of the shocks to predictable changes in sectoral TFP. Both methods produce similar results, and to save space, we only report the results of the max share method in this paper.¹⁴ Figures 1 and 2 present the impulse responses to the shock identified under different values of the finite horizon parameter (h) and the corresponding shares of the forecast error variance in the benchmark system with consumption-sector TFP and investment-sector TFP being the measure of TFP, respectively.

¹¹See Fernald (2010) for more details on all his series. Note that the series obtained from Fernald’s website are produced in June, 2011.

¹²To save upon space, we focus on point estimates. Our main results also hold up qualitatively well when based on confidence-interval inferences.

¹³Our results from the benchmark model are robust to different systems, for instance, a five-variable system which is obtained by dropping investment, output, and the relative price of investment from our benchmark model. The results are also robust to systems with other information variables like a consumer confidence measure, which alleviates a concern about the non-invertibility problem in the presence of anticipated shocks.

¹⁴The results of Barsky and Sims’ method can be found in Figures A.1 and A.2 in the authors’ web appendix.

To make figures more readable, we plot the finite horizon parameter values of $h = 4, 8, 20,$ and 40 quarters as the short-horizon category and $h = 40, 60, 80,$ and 120 quarters as the long-horizon category, separately. Note that the value of the finite horizon of $h = 40$ quarters appears in both categories.

In Figure 1, the first two panels display the impulse responses in the benchmark system with consumption-sector TFP for short- and long-horizon categories, and the last two panels display the corresponding forecast error variance shares. Regardless of the value of the finite horizon parameter h , the impulse responses and forecast error variance shares are nearly identical. Following a favorable shock to predictable changes in consumption-sector TFP, consumption-sector TFP jumps up immediately, and hours, investment, and output all decline significantly on impact. Consumption and stock prices do not respond on impact, but for the long-horizon category, they appear to converge to their new long-run levels. It is worthwhile noting that following our identified shock to predictable changes in consumption-sector TFP, the impulse responses of consumption-sector TFP, hours, investment and output over the first ten quarters are qualitatively the same as those to a favorable news shock to aggregate TFP found in Barsky and Sims (2011). As implicitly indicated by impulse responses, the identified shocks to predictable changes in consumption-sector TFP (in both short- and long-horizon categories) account for a significant share of the forecast error variance (FEV) of hours, investment, and output over the first ten quarters, even if such FEV shares decline slightly when the finite horizon parameter is set to a relatively large number (e.g., 80 and 120 quarters). The share of the FEV of consumption-sector TFP attributable to the identified shock is not affected by the value of the finite horizon parameter (h) used in the max share method.¹⁵ However, the FEV shares of aggregate variables such as hours over short forecast horizons are much larger for small h s than large h s. These results suggest that predictable changes in consumption-sector TFP affect economic fluctuations mainly at short forecast horizons. In sum, the important predictable component of consumption-sector TFP is its short-horizon movements, and anticipated improvements in consumption-sector TFP are associated with decreases in hours, investment, and output over short horizons.

Figure 2 shows the results in the benchmark model with investment-sector TFP for the impulse responses and FEV shares in the short- and long-horizon categories. The resulting impulse responses and forecast error

¹⁵Fernald's adjusted (aggregate or sectoral) TFP series is considered as a measure of the purified exogenous technology process (in all sectors or in each sector). As in Barsky and Sims (2011), we assume that contemporaneous (surprise) shocks to TFP and shocks to predictable changes in TFP together explain all of the FEV of TFP at each forecast horizon. We use this standard to evaluate whether a chosen value of the finite horizon h in the max share method (or H in Barsky and Sims' method) is appropriate to identify shocks to predictable TFP. For a given finite horizon parameter h , we apply the max share method to identify shocks to predictable changes in TFP. Contemporaneous shocks to TFP are identified as innovations in TFP, which are orthogonal to shocks to predictable changes in TFP. If the sum of the FEV shares of TFP attributable to the identified contemporaneous shocks and shocks to predictable changes in TFP is close to one at each forecast horizon, it suggests that we validate our identification assumption and the finite horizon parameter h is an appropriate one to use. For consumption-sector TFP, these two identified shocks explain more than 90% of the FEV of consumption-sector TFP at all forecast horizons up to 40 quarters considered in our calculation. The results for the sum of two FEV shares are presented in Figure A.3 in the authors' web appendix.

variance shares are qualitatively the same for all values of the finite horizon parameter except for two very small values (i.e., $h = 4$ and 8). For instance, in the case with a finite horizon of 40 quarters, investment-sector TFP does not start to rise above zero until eight quarters following a favorable shock to predictable changes in investment-sector TFP, and it eventually converges to a new long-run level. Stock prices, consumption, and the real interest rate all jump immediately, and in particular, consumption continues to increase before settling at a higher new long-run level. Hours, investment, and output barely move on impact of the shock, but increase substantially above zero and reach their peaks before investment-sector TFP starts to rise. The relative price of investment (defined as consumption goods prices divided by investment goods prices) does not move on impact, but rises significantly over horizons, indicating a decline of investment goods prices relative to consumption goods prices.

The identified shocks to predictable changes in investment-sector TFP do not account for much of the FEV of investment-sector TFP for the first eight forecast horizons, but explain most of its FEV at longer forecast horizons, for instance, almost 80% at a horizon of 40 quarters. The identified shocks explain more than 50% of the FEVs of consumption, hours, investment, the relative price of investment, and stock prices at business cycle frequencies. For two very small values of finite horizons parameter ($h = 4$ and 8) in the short-horizon category, however, the FEV share of investment-sector TFP is decreasing with the forecast horizon after the horizon of around 20 quarters. It suggests that the sum of FEV shares of TFP attributable to the identified contemporaneous shocks and shocks to predictable changes in TFP is much less than one if we set h equal 4 or 8 quarters in the max share method. Due to the reason explained in Footnote 15, such small finite horizons parameter values should not be taken as appropriate ones to identify shocks to predictable changes in investment-sector TFP.¹⁶ Therefore, the predictable component of investment-sector TFP is its long-run movements, and a favorable shock to predictable changes in investment-sector TFP induces a broad boom of the economy which proceeds anticipated improvements in investment-sector TFP, which echoes Beaudry and Portier's (2006) finding based on aggregate TFP.

Having understood the relative importance of short- and long-run movements in the predictable components of sectoral TFP series, we now look at how the identification of shocks to predictable changes in aggregate TFP is affected by sectoral TFP in the max share and Barsky and Sims' methods. Figure 3 displays the impulse responses to the shock identified with the max share method and Barsky and Sims'

¹⁶With contemporaneous shocks to TFP identified as innovations in TFP (in other words, given the share of the FEV of TFP attributable to contemporaneous shocks to TFP), the identified shocks to predictable changes in TFP should explain the rest of the FEV of TFP as much as possible. A value of the finite horizon parameter in implementing the max share method (or Barsky and Sims' method) is considered appropriate if the sum of FEV shares of TFP attributable to identified contemporaneous shocks and shocks to predictable changes in TFP is close to one at each forecast horizon up to a truncation horizon. See Figure A.3 in the authors' web appendix for the results for the sum of two FEV shares in the case of investment-sector TFP.

method in the benchmark system with either aggregate TFP or each sectoral TFP.¹⁷ The first two panels show the results from the max share method for two different values of the finite horizon parameters, $h = 40$ and 80 , respectively, and the last two panels present the results from Barsky and Sims' method for two different values of the finite truncation horizon, $H = 40$ and 80 , respectively. In each panel, we presents three sets of impulse responses for the benchmark models with aggregate TFP, investment-sector TFP, and consumption-sector TFP. In the below, we describe the results shown in Figure 3, focusing on identified shocks to predictable changes in aggregate TFP.

First, for both the max share and Barsky and Sims' methods with the finite (truncation) horizon of 80 quarters, aggregate TFP does not start to rise until 8 to 10 quarters following a favorable shock to predictable aggregate TFP, which echoes the response of investment-sector TFP to a favorable shock to investment-sector TFP. Aggregate TFP eventually converges to its new long-run level that is much lower than that of investment-sector TFP following a favorable shock to predictable changes in investment-sector TFP. The impulse responses of aggregate variables including stock prices and the relative price of investment to a shock to predictable changes in aggregate TFP over all horizons are almost identical to those to a shock to investment-sector TFP. These results suggest that both max share and Barsky and Sims' methods with a relatively long horizon consistently pick up the long-run predictable component of investment-sector TFP that dominates the identification of shocks to predictable changes in aggregate TFP.

Second, the results for the finite horizon of 40 quarters indicate that the identification of shocks to predictable aggregate TFP is affected by the short-run predictable component of consumption-sector TFP in this case.¹⁸ In particular, Barsky and Sims' method is designed to consider short- and long-horizon predictable components of aggregate TFP, and thus the identification of shocks to predictable aggregate TFP under this method is more likely to be affected by the short-run predictable component of consumption-sector TFP. As a result, in the third panel of Figure 3, a favorable shock to predictable aggregate TFP leads to decreases in hours, investment, and output on impact and an immediate increase in aggregate TFP, which is qualitatively the same as the effect of a favorable shock to predictable changes in consumption-sector TFP.

As a robustness check, we consider a VAR system with all three TFP series, (i.e., a system with aggregate TFP, investment-sector TFP, consumption-sector TFP, stock prices, consumption, the real interest rate, hours, and the relative price of investment). The shocks to predictable aggregate TFP or shocks to predictable investment-sector TFP are identified by employing both the max share and Barsky and Sims' methods for three values of the finite horizon parameter: 20, 40, and 80 quarters.¹⁹ These results for the impulse responses

¹⁷The corresponding forecast error variance shares are presented in Figure A.4 in the authors' web appendix.

¹⁸Barsky and Sims (2011) use the finite truncation horizon of 40 quarters.

¹⁹A constant and four lags are also included in this VAR model. When identifying shocks to predictable changes in (aggregate

are presented in Figure 4.²⁰ The results are consistent with our findings in the benchmark model.²¹ It is worth noting that a favorable shock to predictable changes in investment-sector TFP appears to lead to declines in consumption-sector TFP over short horizons.

4 Conclusion

In this paper, we study the effect of shocks to predictable changes in sectoral TFP on business cycle fluctuations. We find that predictable improvements in investment-sector TFP are mainly at long forecast horizons and induce a broad economic boom, while predictable improvements in consumption-sector TFP occur at short forecast horizons and are associated with immediate declines in hours worked, investment, and output. We argue that this difference reconciles the seemingly contradictory findings in Beaudry and Portier (2006) and Barsky and Sims (2011). The long-run restrictions method used in Beaudry and Portier aims at long-run movements in aggregate TFP, which exclusively picks up the effect of shocks to predictable movements in investment-sector TFP. The method proposed by Barsky and Sims is designed to consider both short- and long-run predictable changes in aggregate TFP, and thus the associated responses of macro variables and aggregate TFP over short horizons are likely to be affected by shocks to predictable movements in consumption-sector TFP, especially when the truncation horizon for implementing their proposed method is set to a relatively short one. We believe such differences explain why Beaudry and Portier (2006) find that their identified favorable shocks to predictable changes in aggregate TFP are expansionary and lead to delayed improvements in aggregate TFP, while Barsky and Sims (2011) find that their identified shocks fail to generate broad-based economic comovements and lead to immediate changes in aggregate TFP.

In addition, we find that shocks to predictable changes in investment-sector TFP are much more important in driving economic fluctuations at business cycle frequencies than shocks to predictable changes in consumption-sector TFP. Besides reconciling the seemingly contradictory findings in Beaudry and Portier (2006) and Barsky and Sims (2011), our results call for further theoretical studies on this issue. Can standard real business cycle models replicate our finding that predictable improvements in investment-sector TFP induce a broad economic boom that leads actual increases in TFP 6 to 8 quarters? Are these models also consistent with our finding that shocks to predictable changes in consumption-sector TFP are mainly

or investment-sector) TFP, we impose the zero restriction on the impact response of its own TFP only and leave two other TFP series unrestricted. However, since two sectoral TFP are components of aggregate TFP, it would be more appropriate to impose the zero restrictions on all three TFP when identifying shocks to predictable changes in aggregate TFP. Imposing such a zero restriction does not change the results. See Figure A.5 in the authors' web appendix.

²⁰The corresponding forecast error variance shares are presented in Figure A.6 in the authors' web appendix.

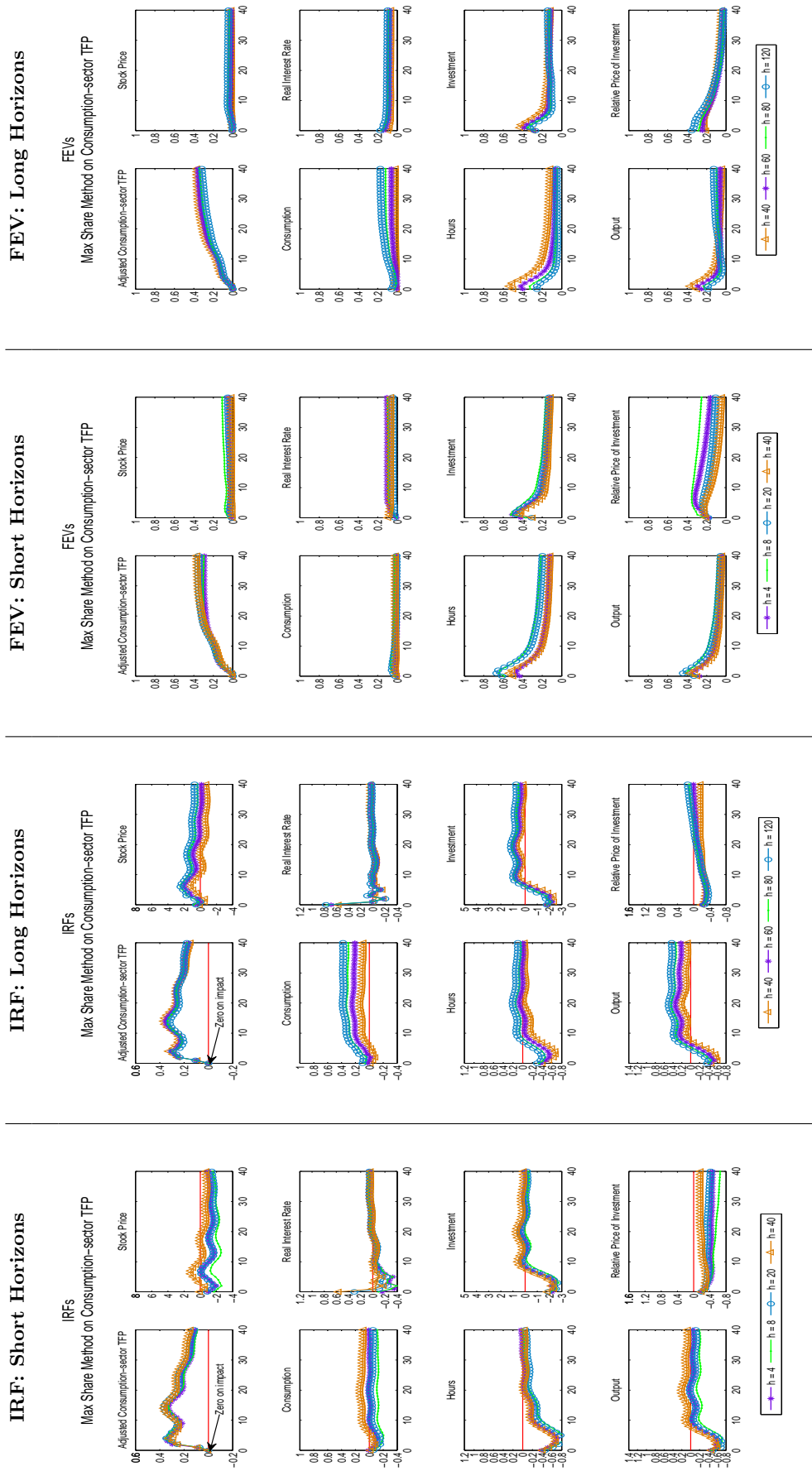
²¹In the case of the finite horizon of 20 quarters, the results for aggregate TFP would imply what would be obtained when applying on consumption-sector TFP, which are presented in Figure A.7 in the authors' web appendix.

contractionary? Can they also replicate that shocks to predictable changes in investment-sector TFP are much more important in driving business cycles than those in consumption-sector TFP? We leave these questions for the future research.

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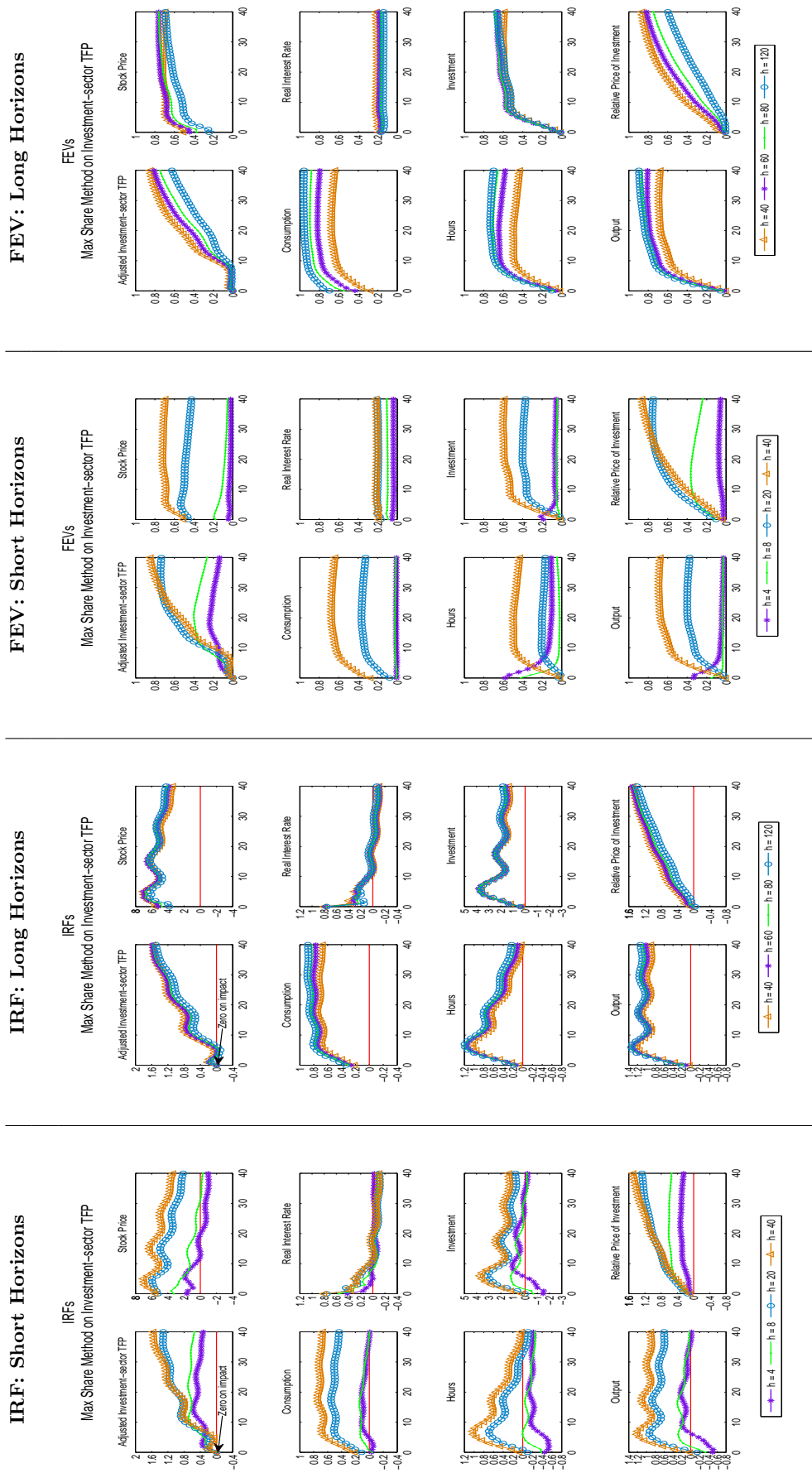
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Figure 1: Max Share Method with Varying Finite Horizon in the Benchmark System with Consumption-sector TFP as a Measure of TFP



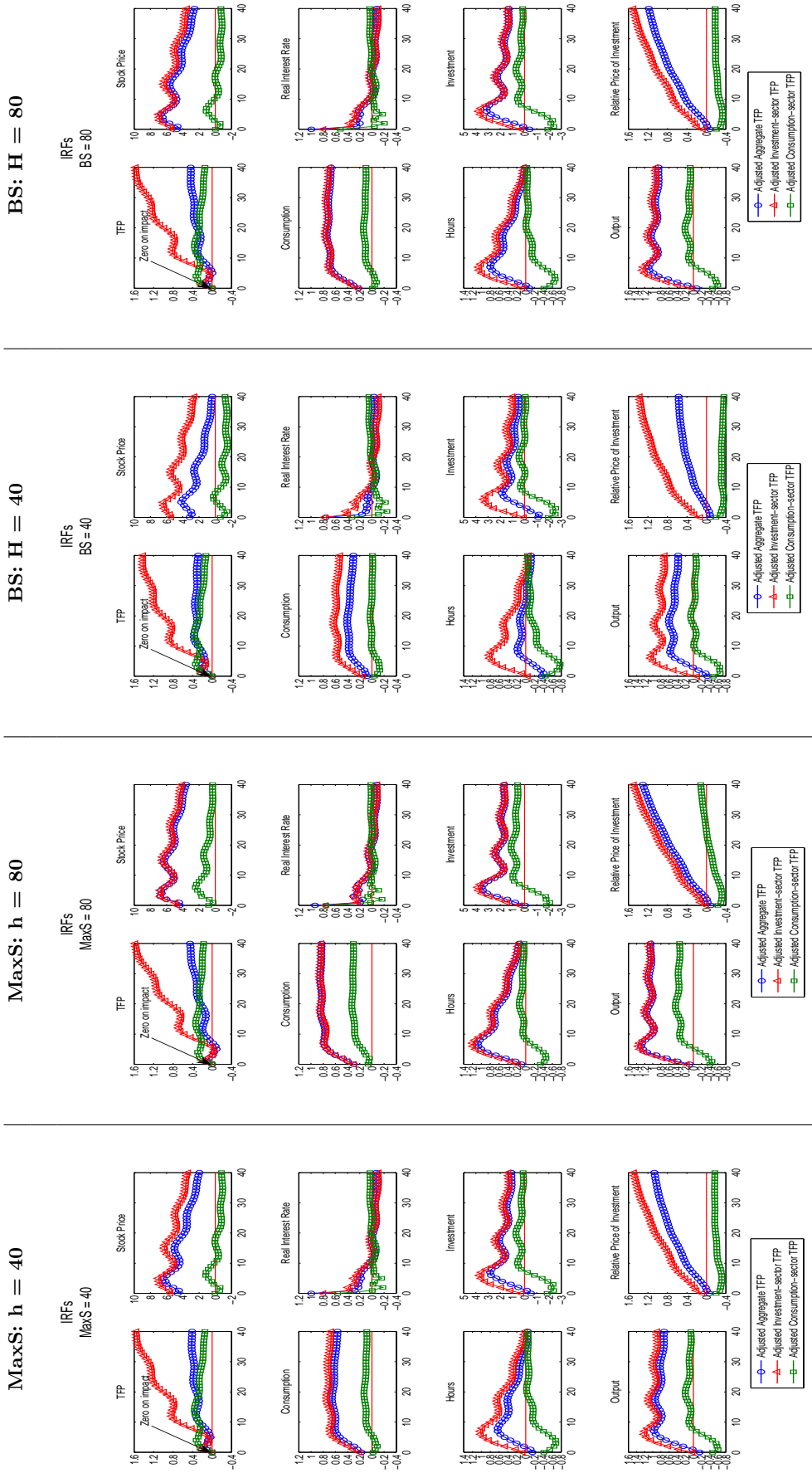
This figure has four panels. The first panel (the second panel) displays OLS point estimates of impulse responses to a positive unit shock identified with the Max Share Method with the finite horizon $h = 4, 8, 20$ and 40 quarters ($h = 40, 60, 80,$ and 120 quarters), respectively, in the benchmark eight-variable system with consumption-sector TFP as a measure of TFP. The third panel (the fourth panel) displays OLS point estimates of forecast error variance shares attributable to that shock that correspond to the first panel (the second panel). For the first two panels, the unit of the vertical axis is percentage deviation from the situation without shock, and for all panels, the unit of the horizontal axis is the number of quarters following the shock.

Figure 2: Max Share Method with Varying Finite Horizon in the Benchmark System with Investment-sector TFP as a Measure of TFP



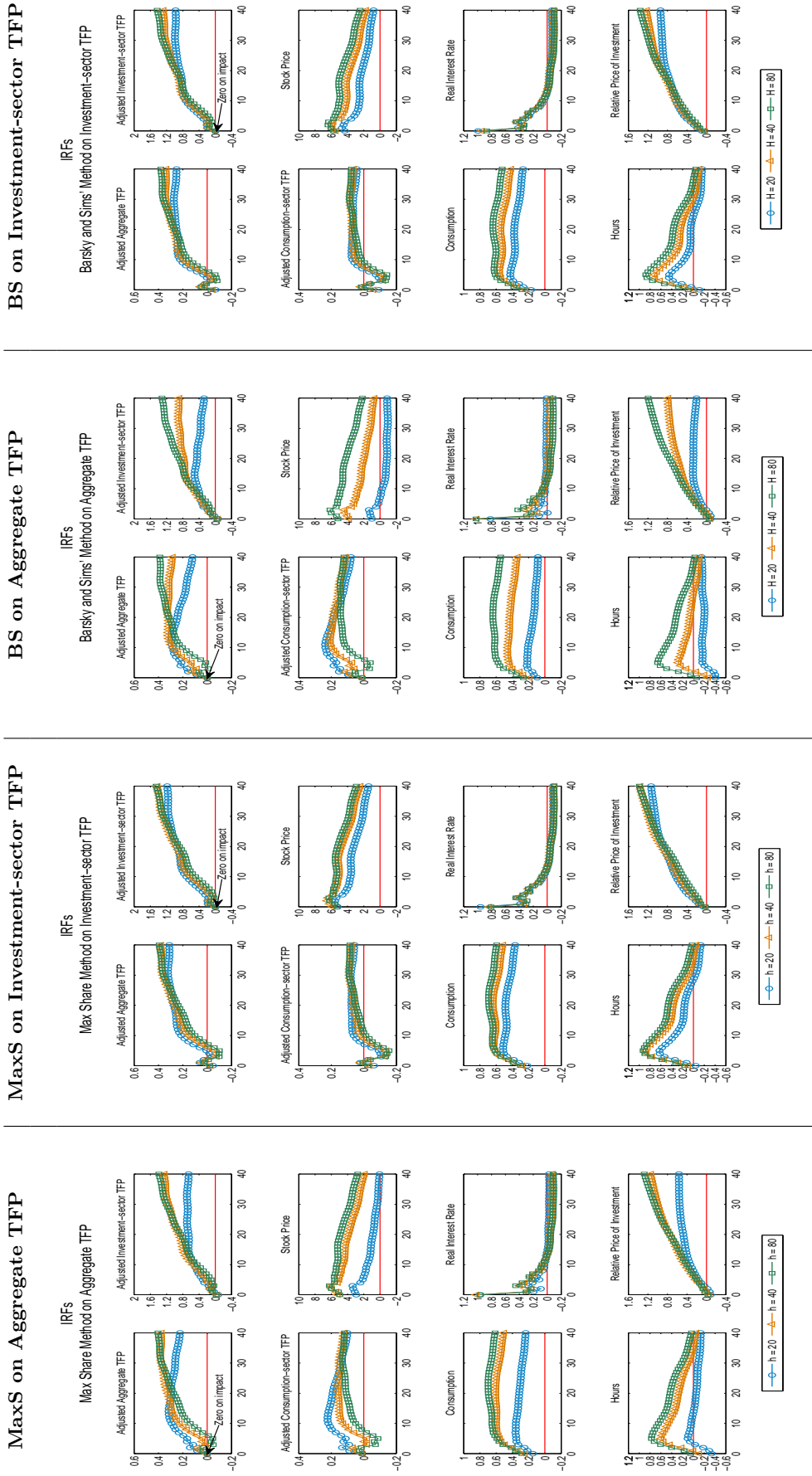
This figure has four panels. The first panel (the second panel) displays OLS point estimates of impulse responses to a positive unit shock identified with the Max Share Method with investment-sector TFP as a measure of TFP. The third panel (the fourth panel) displays OLS point estimates of forecast error variance shares attributable to that shock that correspond to the first panel (the second panel). For the first two panels, the unit of the vertical axis is percentage deviation from the situation without shock, and for all panels, the unit of the horizontal axis is the number of quarters following the shock.

Figure 3: Impulse Responses to a Positive Shock Identified with the Max Share and Barsky and Sims' Methods in the Benchmark System



This figure has four panels, each of which displays OLS point estimates of impulse responses to a positive unit identified predictable TFP shock in the benchmark eight-variable system with either aggregate TFP, investment-sector TFP, or consumption-sector TFP as a measure of TFP, and thus each panel has three sets of impulse responses. The first two panels (the last two panels) are impulse responses to the shock identified by applying the Max Share Method denoted by MaxS (Barsky and Sims' Method denoted by BS) on TFP for the finite horizon h (the finite truncation horizon H) of 40 and 80 quarters, respectively. The unit of the vertical axis is percentage deviation from the situation without shock and the unit of the horizontal axis is the number of quarters following the shock.

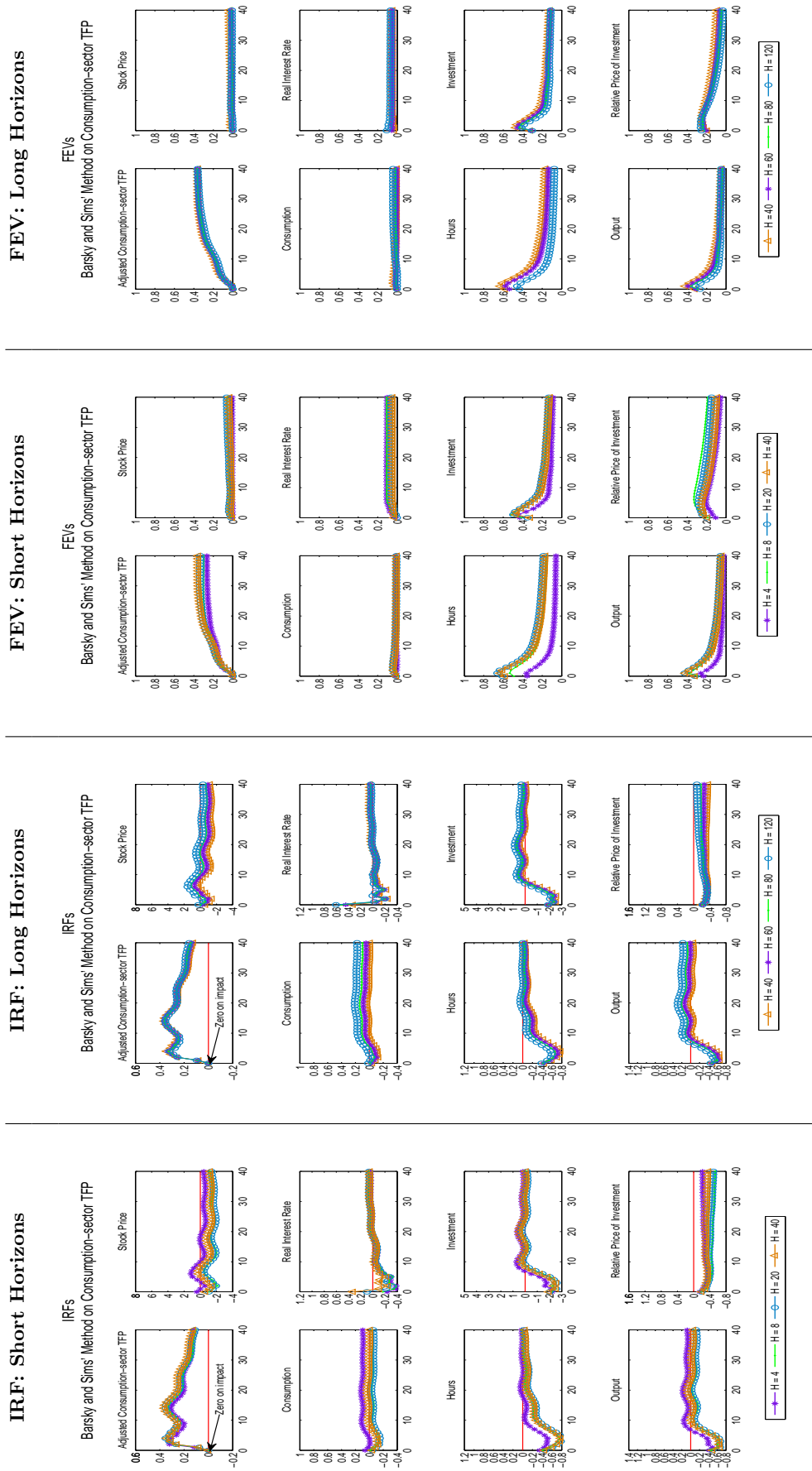
Figure 4: Max Share and Basky and Sims' Methods on either Aggregate TFP or Investment-sector TFP in the System with Aggregate TFP and Sectoral TFP



This figure has four panels, each of which displays OLS point estimates of impulse responses to a positive unit shock identified by applying the Max Share and Basky and Sims' methods on aggregate TFP (the first and third panels) or investment-sector TFP (the second and fourth panels) for three values of the finite horizon (h/H) of 20, 40, and 80 quarters, respectively, in the eight-variable system with (Aggregate TFP, Investment-sector TFP, Consumption-sector TFP, Stock Price, Consumption, Real Interest Rate, Hours). Note that the zero restriction on the impact response of its own TFP only is imposed. The unit of the vertical axis is percentage deviation from the situation without shock and the unit of the horizontal axis is the number of quarters following the shock.

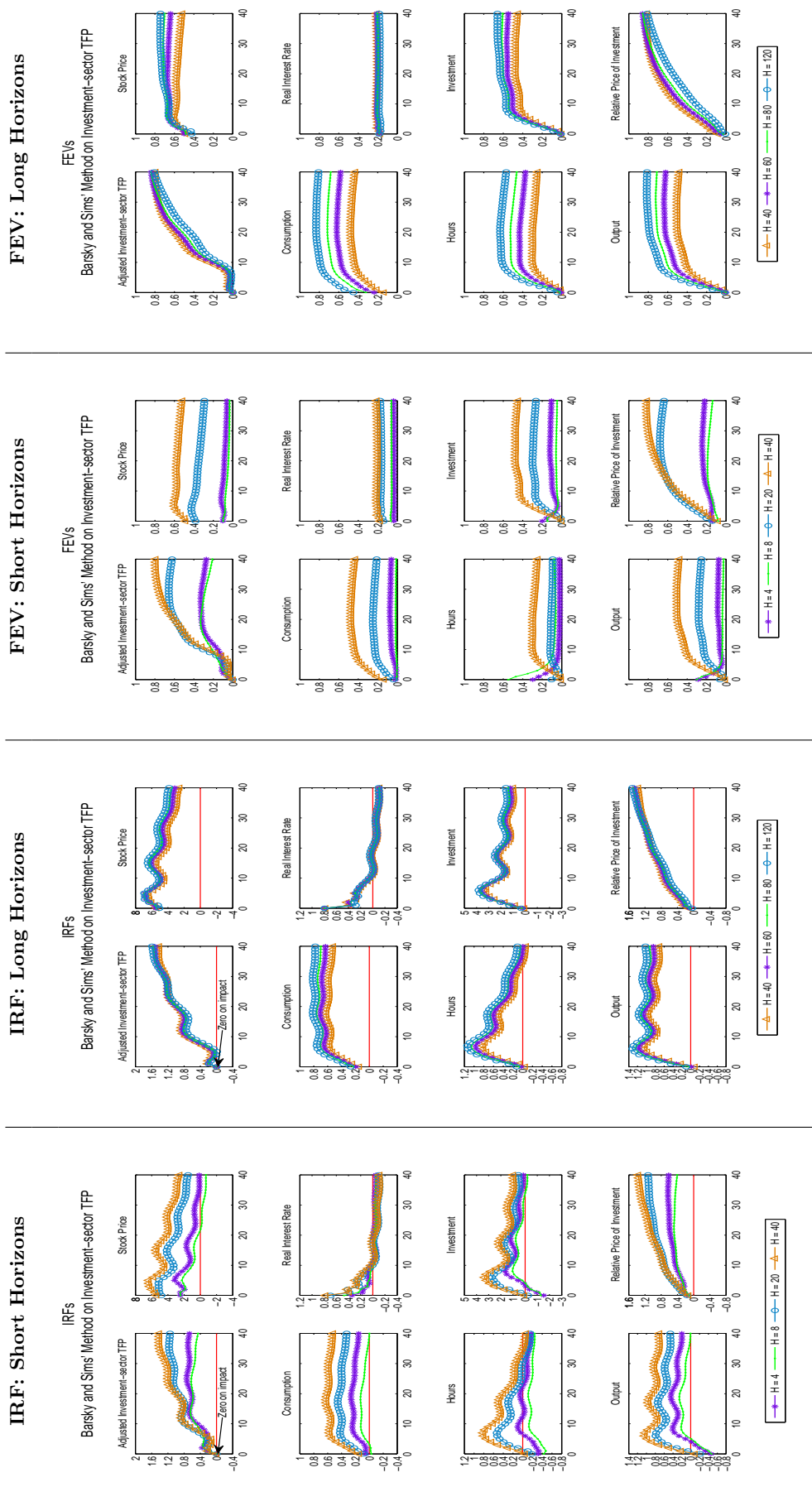
A APPENDIX: Supplemental Figures (not for publication)

Figure A.1: Barsky and Sims' Method with Varying Finite Horizon in the Benchmark System with Consumption-sector TFP as a Measure of TFP



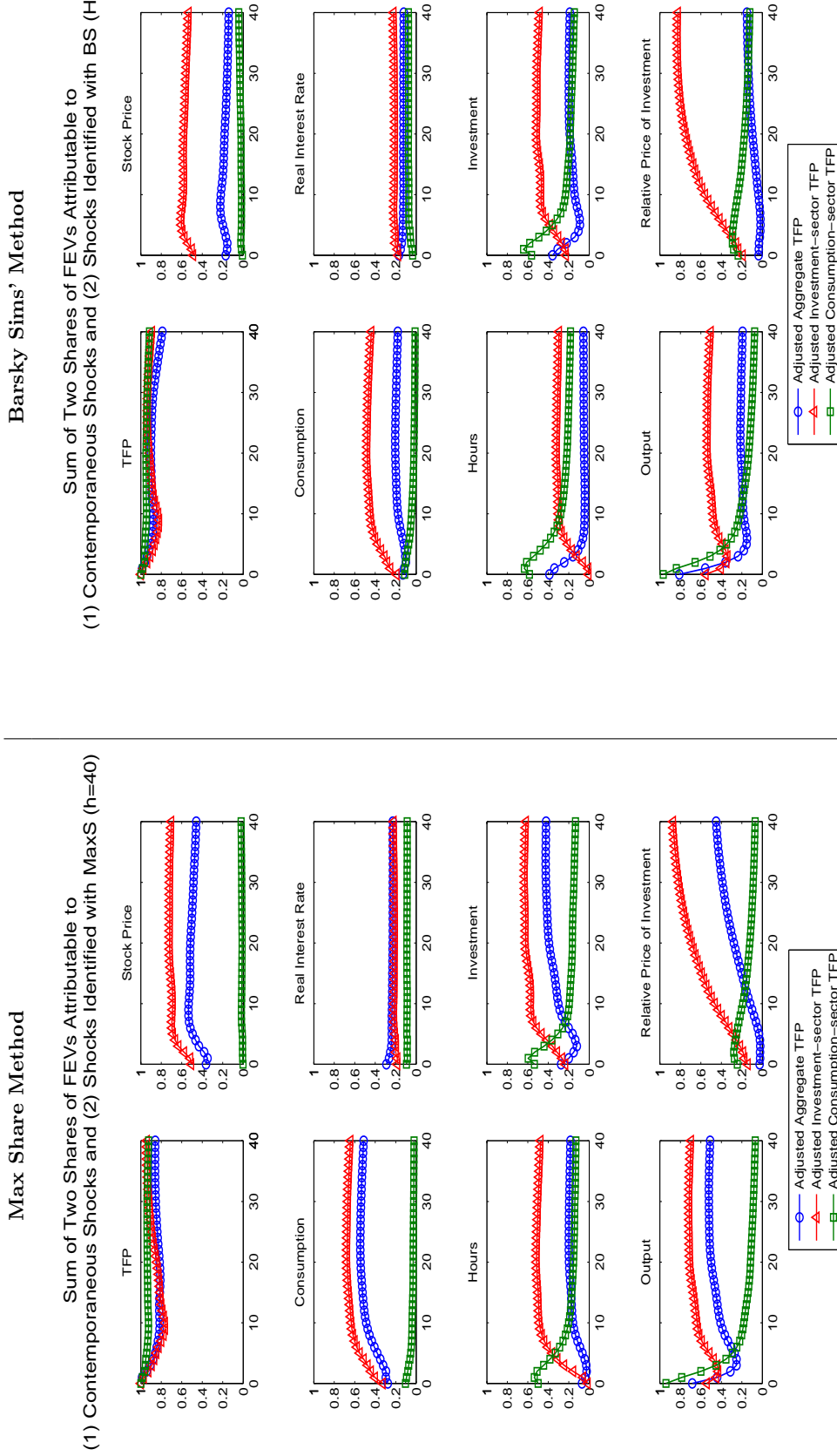
This figure has four panels. The first panel (the second panel) displays OLS point estimates of impulse responses to a positive unit shock identified with Barsky and Sims' Method with the finite horizon $h = 4, 8, 20$ and 40 quarters ($h = 40, 60, 80,$ and 120 quarters), respectively, in the benchmark eight-variable system with consumption-sector TFP as a measure of TFP. The third panel (the fourth panel) displays OLS point estimates of forecast error variance shares attributable to that shock that correspond to the first panel (the second panel). For the first two panels, the unit of the vertical axis is percentage deviation from the situation without shock, and for all panels, the unit of the horizontal axis is the number of quarters following the shock.

Figure A.2: Barsky and Sims' Method with Varying Finite Horizon in the Benchmark System with Investment-sector TFP as a Measure of TFP



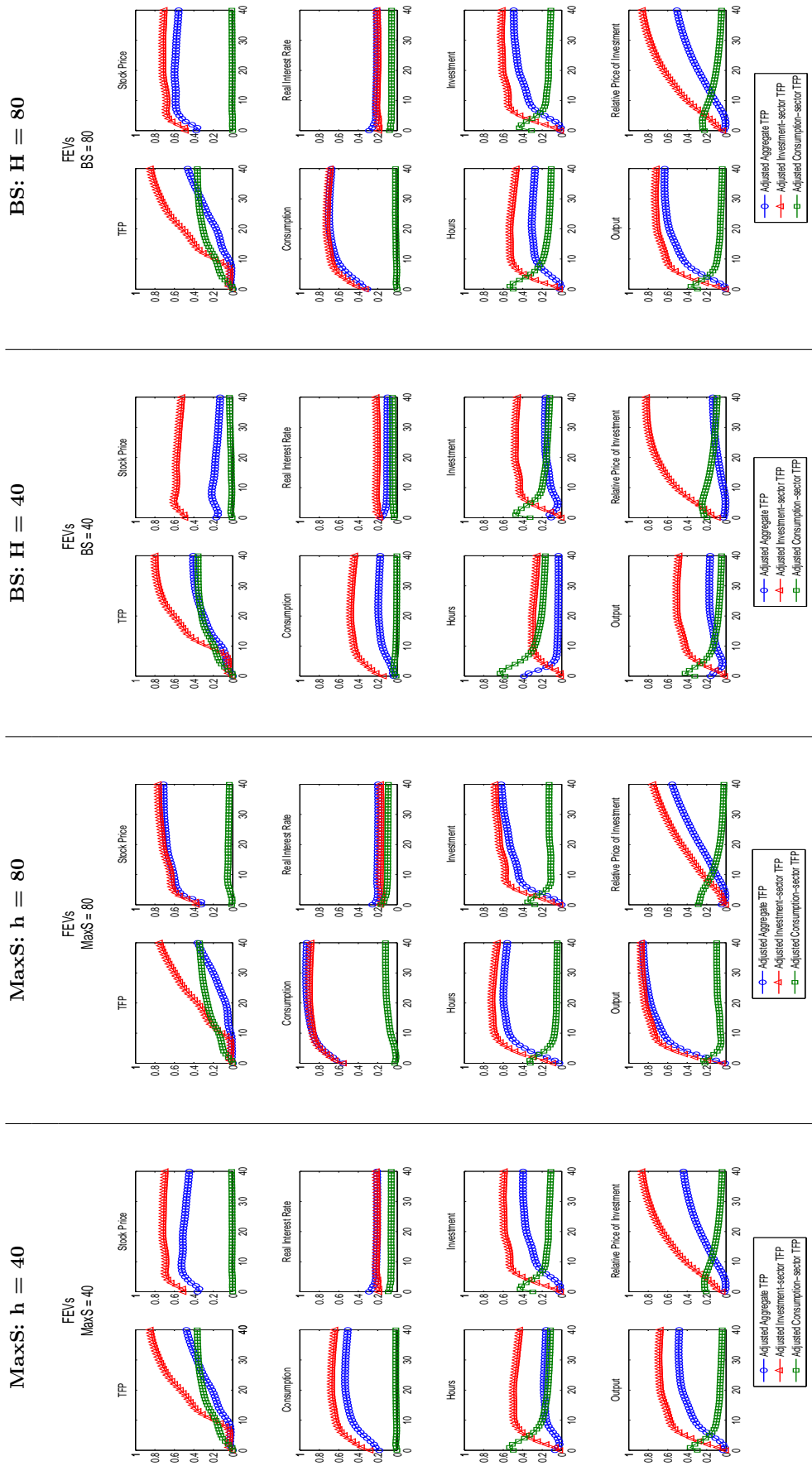
This figure has four panels. The first panel (the second panel) displays OLS point estimates of impulse responses to a positive unit shock identified with Barsky and Sims' Method with the finite horizon $h = 4, 8, 20$ and 40 quarters ($h = 40, 60, 80,$ and 120 quarters), respectively, in the benchmark eight-variable system with investment-sector TFP as a measure of TFP. The third panel (the fourth panel) displays OLS point estimates of forecast error variance shares attributable to that shock that correspond to the first panel (the second panel). For the first two panels, the unit of the vertical axis is percentage deviation from the situation without shock, and for all panels, the unit of the horizontal axis is the number of quarters following the shock.

Figure A.3: The Sum of Forecast Error Variance Shares Attributable to Contemporaneous Shocks to TFP and to Predictable TFP Shocks in the Benchmark System



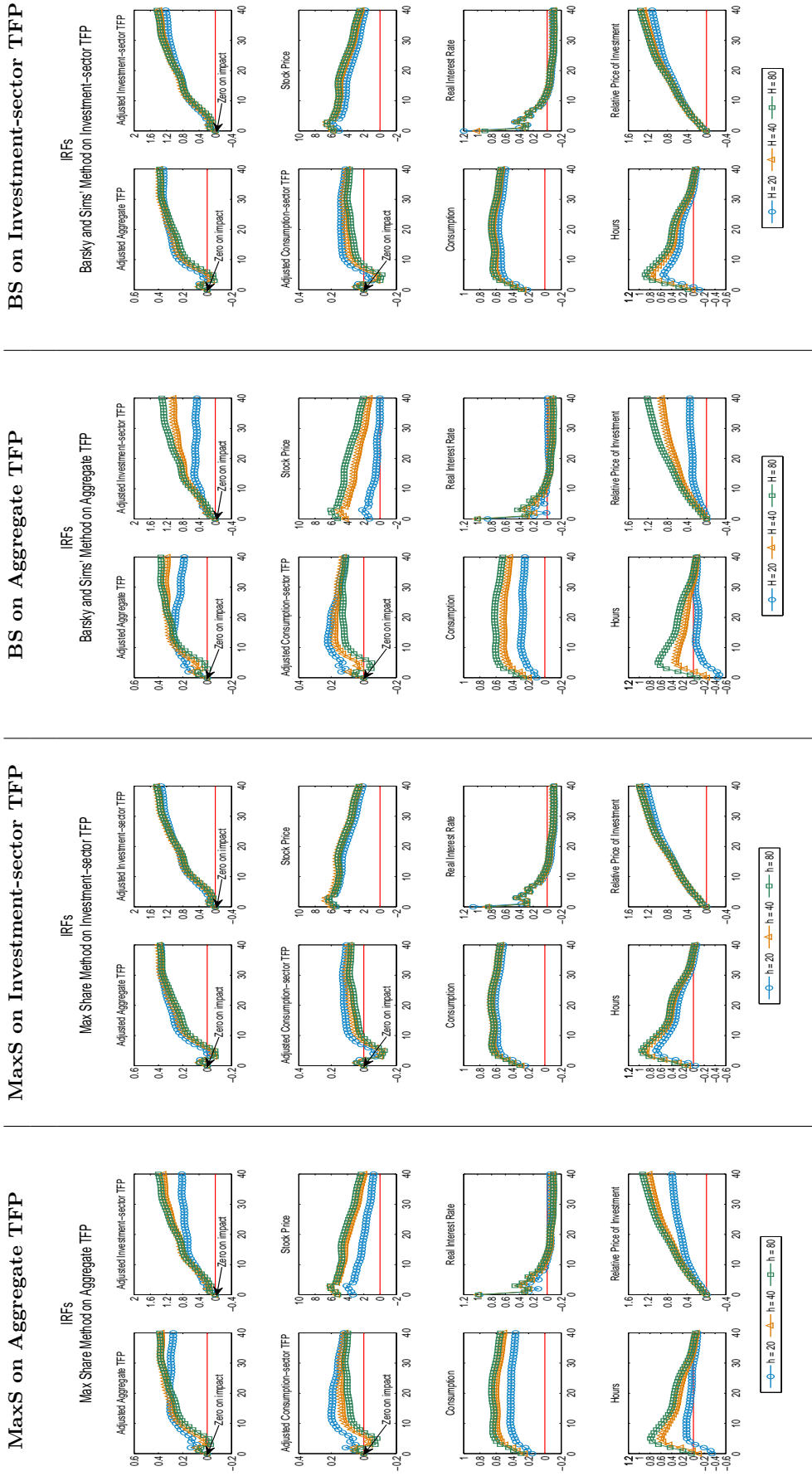
This figure has two panels, each of which displays OLS point estimates of the sum of the shares of the forecast error variances attributable to contemporaneous shocks to TFP identified as innovations in TFP and to shocks to predictable TFP identified with the Max Share Method with $h = 40$ (the left panel) or Barsky and Sims' method with $H = 40$ (the right panel) in the benchmark system.

Figure A.4: Forecast Error Variance Shares Attributable to Shocks Identified with the Max Share and Barsky and Sims' Methods in the Benchmark System



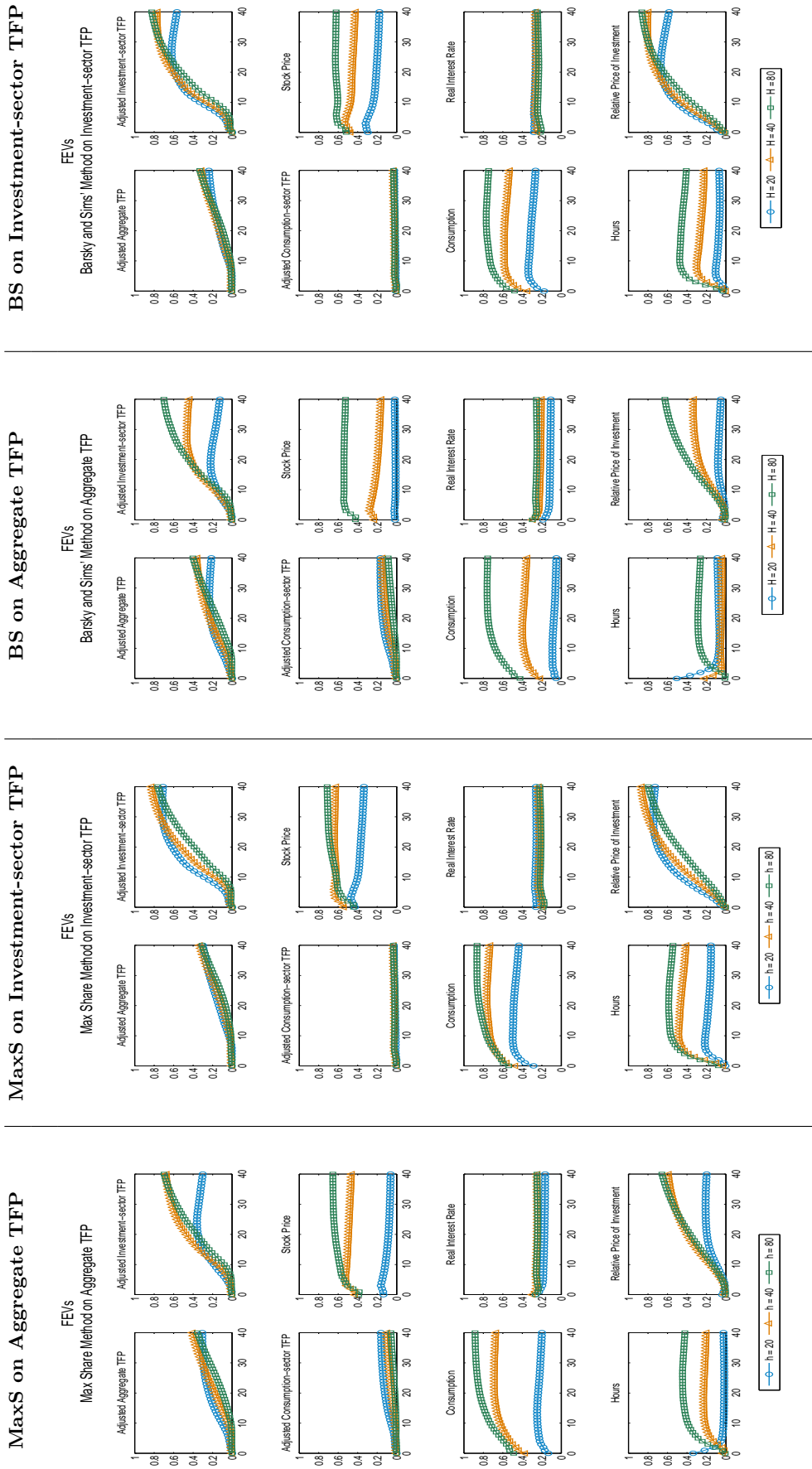
This figure displays OLS point estimates of forecast error variance shares that correspond to impulse responses shown in Figure 3 in the text.

Figure A.5: Max Share and Barsky and Sims' Methods with the Zero Restrictions on All TFP in the System with Aggregate TFP and Sectoral TFP



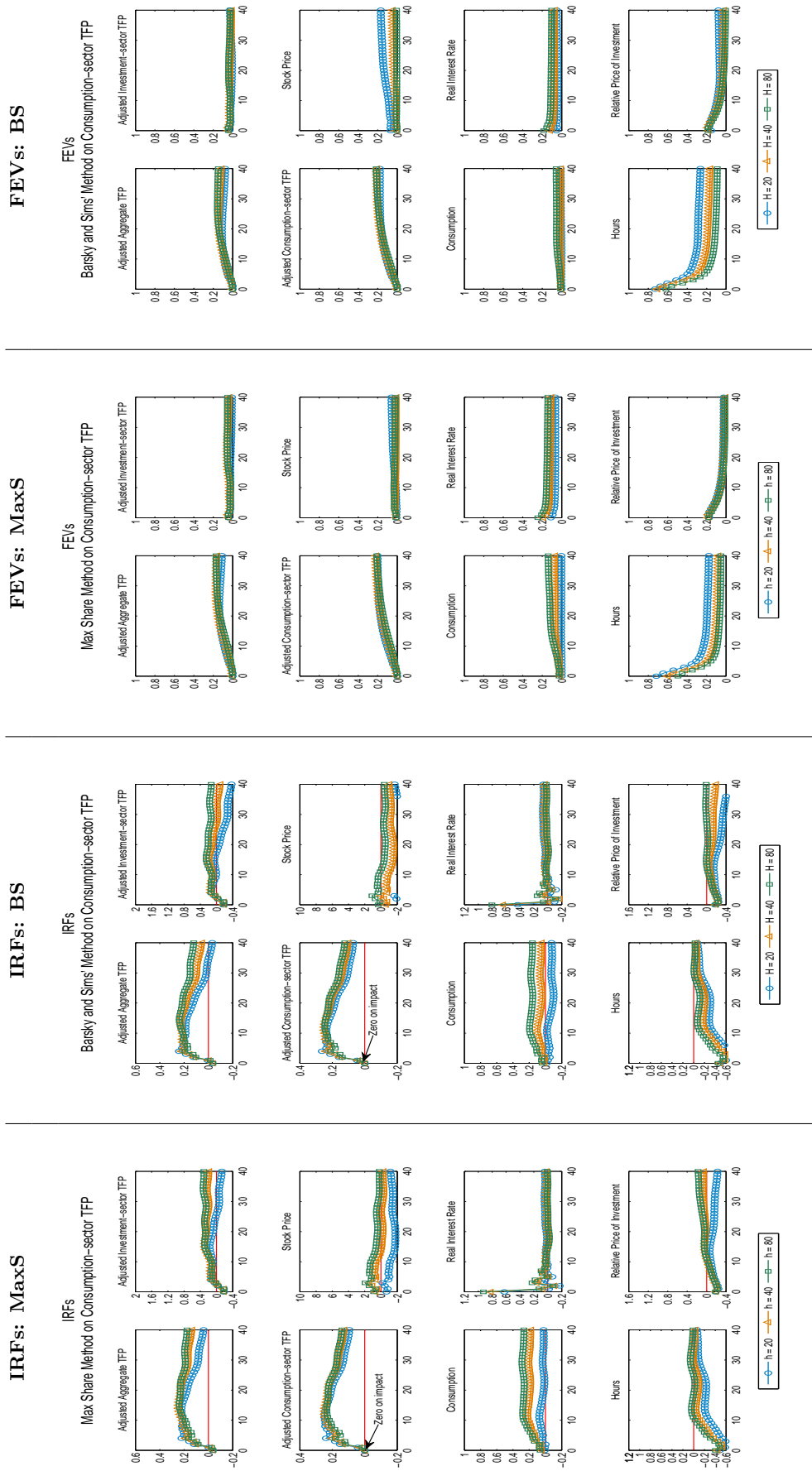
This figure displays OLS point estimates of impulse responses, identified as in Figure 4 in the text, but the zero restrictions that the impact responses of all aggregate, investment-sector, consumption-sector TFP are zero are imposed.

Figure A.6: Forecast Error Variance Shares: Max Share and Barsky and Sims' Methods on either Aggregate TFP or Investment-sector TFP in the System with Aggregate TFP and Sectoral TFP



This figure displays forecast error variance shares that correspond to impulse responses shown in Figure 4 in the text.

Figure A.7: Max Share and Barsky and Sims' Methods on Consumption-sector TFP in the System with Aggregate TFP and Sectoral TFP



This figure displays impulse responses and forecast error variance shares estimated when applying the Max Share and Barsky and Sims' methods on consumption-sector TFP in the system with aggregate and sectoral TFP. Note that the zero restriction on the impact response of consumption-sector TFP only is imposed.