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News-driven Business Cycles in SVARs

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Abstract

Recent studies proposed news about future technology growth as the main driver of macroeconomic fluctuations. The identification of these news through stock prices in SVARs has been criticized in the past. Therefore, I propose a series of experiments to test that hypothesis by examining its implications. If business cycles are mainly driven by news then these shocks should be captured by other time series as well. I find that news shocks identified through S&P 500 prices exhibit the same dynamics as news identified through a broader stock price index, patent applications, the relative price of investment or shocks to the real interest rate. The common theme among these identifications is a technological change in productivity that demands time to build, economic activity and natural resources to come into effect.

JEL: E30, E32
Keywords: Business Cycles, News Shocks, Technological Progress

Since the work of Pigou (1927) and Keynes (1936), expectations are known to be an important factor in economic fluctuations. The asset pricing theory suggests that expectations of future output affect expected future cash flows on the company level which are in turn an important factor in the estimation of a company's value. This implication is consistent with econometric analysis that usually finds a strong correlation

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of approximately 0.7 between current stock prices and future output.[1] Correspondingly, the descriptive business cycle analysis, pioneered by Burns and Mitchell (1946), clearly identifies stock market prices as a leading indicator of economic activity.[2]

Subsequently, Beaudry and Portier (2006) introduce a novel identification scheme which exploits the relation between stock market prices and the anticipated changes in output. They compare two identification schemes which differ only in the definition of news shocks in a bivariate structured vector error correction model with one cointegrating relationship containing output and stock prices. While in the first identification scheme news shocks are identified by the innovations in stock prices that are orthogonal to the innovations of TFP, the second scheme assumes that news shocks are the innovations that drive long-run movements in TFP. The comparison of these two innovations delivers one main result: These two separately measured innovations are almost perfectly colinear and induce the same impulse response dynamics.[3] They base their identification of news shocks as anticipated TFP shocks on the assumption that technological innovation needs time to be implemented. Computing forecast error variance decompositions, they conclude that the common component of both shocks represents an anticipated TFP shock that can explain more than 50% of the business cycle fluctuations in consumption, hours and investment. In addition, the impulse responses deliver rich dynamics in the first 12 quarters after the shock, beginning with a strong temporary boom followed by a mild recession which in turn is superseded by a period of substantial growth, a description that resembles common stylized facts on the business cycle.[4] Likewise, Schmitt-Grohe and Uribe (2008 estimate a DSGE model that contains various types of news shocks with Bayesian methods and find that news shocks account for more than two-thirds of the economic fluctuations.

These results, on the relatively high importance of anticipated TFP shocks, contrast the high importance of surprise changes in TFP for business cycle fluctuations predicted by standard RBC models. Moreover, these results do not assign a big role to investment specific technology changes which contradicts the results of Fisher (2006). Beaudry and Lucke (2010) address these conflicting results by proposing a larger structural vector error correction model (SVECM) that explicitly incorporates both, the relative price of investment and the anticipated TFP shock. They show that while in absence of stock prices the IST shock is important in explaining TFP variance, introducing stock prices

[1]Fama (1990) provides evidence for United States. The correlation in the quarterly sample of 1948 to 2008 used in this work is 0.695.

[2]This method relies heavily on the correct identification of the peaks and throughs in the Business Cycle. A common procedure can be found in Bry and Boschan (1971).

[3]Beaudry and Portier (2006) estimate the correlation between these two news shocks to be 0.989 with a standard deviation of 0.025.

[4]Beaudry and Portier (2006) Figure 9

into the SVECM does reduce the relative importance of IST shocks for forecasted TFP to negligible values coupled with high importance of the anticipated TFP shock, which increases over time. The result is consistent with the view that anticipated TFP shocks affect stock markets before they affect the relative price of investment goods, but leaves the question of the cause of news shocks open.

These findings imply an important role of news shocks for economic fluctuations without defining the actual nature of this shock. I propose in the following a series of experiments inferred from common economic beliefs about relations among economic variables. I will compare the dynamics of different news shock identification schemes to a baseline news shock SVAR model as presented in Beaudry and Lucke [2010].

1 The Vector Error Correction Framework

Sims (1980) proposed a simple framework to capture the rich dynamics between multiple macroeconomic time series. This framework expands the linear autoregressive equation to account for n variables. If one assumes a finite number of lags to influence the current value of a variable, one can express this variable as the weighted sum of up to p past values of itself and the p past values of all other variables within the system. The Vector Autoregression of order p (VAR(p)) takes the following form:[5]

$$y_t = \nu + \sum_{i=1}^{p} A_i y_{t-i} + u_t \qquad \text{VAR(p)} \tag{1}$$

where y_t is the vector of variables, ν is a deterministic term, the A_i's are $n \times n$ coefficient matrices and u_t is a $n \times 1$ vector of unobservable error terms. Assuming that u_t is a zero mean independent white noise process with a time invariant, positive definite covariance matrix Σ_u, the process is stable, if:

$$det(I_n - \sum_{i=1}^{p} A_i z^i) \neq 0 \qquad \text{for } |z| \leq 1, \tag{2}$$

i.e. the determinant of the autoregressive operator has no roots in nor on the complex unit circle. If the polynomial has a unit root then at least some variables are integrated. If some of the integrated variables share a common stochastic trend, i.e. there exists a linear combination of them that is integrated of order zero (I(0)), the variables included in this linear combination with a non-zero weight are called cointegrated. Granger (1981) argued that using linear regressions on de-trended non-stationary time series

[5] This derivation is based on Lütkepohl (2004) p.88 et seq. and Lütkepohl (2005) p. 237 et seq.

data can lead to spurious correlation. Since the focus of this work lies on the behavior and influence of stock prices which are often proposed to follow a random walk, hence being non-stationary, I will explicitly allow for integrated variables.[6] The vector error correction model (VECM) form is given by:

$$\Delta y_t = \nu + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + u_t \qquad VECM(p-1), \tag{3}$$

where $\Gamma_i := -\sum_{j=i+1}^{p} A_j$ and $\Pi := (\sum_{i=1}^{p} A_i - I_n)$. Since Δy_t and u_t are I(0) for all t, we can infer that Πy_{t-1} is the only term that includes variables of order one, namely y_{t-1}, assuming that any integrated variable is at most of order one. But since the VECM(p-1) equation holds, it must be that Πy_{t-1} is I(0). Therefore, the VECM representation is I(0) and thus stationary and all cointegrating relations are represented in Πy_{t-1} which will be referred to as the long-run part, while the Γ_i will be referred to as the short-run parameters.

Assuming variables to be integrated of order one, the underlying VAR(p) process has unit roots and hence Π will not be invertible since it does not have a full rank n. Therefore, suppose the rank of Π to be $r < n$. Then $\Pi = \alpha\beta'$ holds for some α and β with rank r. It follows that $\beta' y_{t-1}$ contains r independent cointegrating relations among the n components of y since premultiplying an I(0) process by any matrix, e.g. $(\alpha'\alpha)^{-1}\alpha'$, conserves the integration property and therefore the following holds: $(\alpha'\alpha)^{-1}\alpha'\Pi = \beta' y_{t-1}$. Thus β will be referred to as cointegration matrix and α as loading matrix since it contains the weights attached to the cointegrating relations.[7]

I will impose in the following the Granger Representation Theorem proposed by Johansen (1991).[8]

Proposition: Suppose $\Delta y_t = \alpha\beta' y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + u_t$, where $y_t = 0 \ \forall \ t \leq 0$, u_t is white noise for $t = 1, 2, ...$, and $u_t = 0$ and let the following condition hold for the parameters:
(a) The roots of the characteristic polynomial $det[\alpha\beta' y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + u_t] = 0$ are either outside the unit circle or equal to one.[9]
(b) The matrix Π has reduced rank $r < n$ and can be expressed as the product $\Pi = \alpha\beta'$ of two $n \times r$ matrices of rank r.
(c) The matrix $\alpha'_{\perp}(I_n - \sum_{i=1}^{p-1} \Gamma_i)\beta_{\perp}$ has full rank where $\alpha_{\perp}$ and $\beta_{\perp}$ are the orthogonal complements to α and β.

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[6] See Fama (1965) for a discussion on the random walk behavior of stock market prices.

[7] The matrices are not unique since given any non-singular square $r \times r$ matrix C the new loading matrix αC and cointegration matrix βC^{-1} satisfy the same restriction $\Pi = \alpha C C^{-1} \beta'$

[8] A proof can be found in Hansen (2005)

[9] The exclusion of roots inside the unit circle may be justified due to their higly explosive behavoir.

Then, y_t has the representation

$$y_t = \Xi \sum_{i=1}^{t} u_i + \sum_{j=0}^{\infty} \Xi_j^* u_{t-j} + y_0^* \tag{4}$$

where $\Xi = \beta_\perp[\alpha'_\perp(I_n - \sum_{i=1}^{p-1} \Gamma_i)\beta_\perp]^{-1}\alpha'_\perp$, $\sum_{j=0}^{\infty} \Xi_j^* u_{t-j}$ is an I(0) process and y_0^* contains initial values.

This representation is the multivariate version of the Beveridge-Nelson (1981) decomposition of y_t. It decomposes the integrated process y_t into the n-r stochastic trends $\Xi \sum_{i=1}^{t} u_i$, the I(0) process $\Xi^*(L)u_t$ and the initial condition. Then, the first assumption ensures that the process is not explosive. The second assumption induces cointegration whenever $r \geq 1$. This ensures at least n-r unit roots and combined with the third assumption ensures that there are exactly n-r unit roots, hence restricting the process from being I(2). Deterministic terms may be added, although their nature may differ fundamentally from the stable VARs. An intercept in an integrated process may just be constant, a linear trend term or seasonal dummies. A constant term can be absorbed into an intercept within the cointegration relation, while the inclusion of a linear trend might even generate quadratic trends in the means of the variables.[10]

VARs are reduced-form models with the ability to describe dynamic properties of data. As pointed out earlier, the interpretation of the impulse responses can be problematic, if the components of the forecast error are significantly correlated. Unfortunately, a diagonal covariance matrix is in practice unlikely. Therefore the Lucas critique applies as long as these data sets are not linked to deep parameters which characterize preferences and available technologies. Structural VARs impose assumptions to connect the observed VAR forecast errors to structural innovations associated with economic theory.

A variety of structural VAR models are used in the macroeconometric literature.

Since most research on SVECMs focuses on the interpretation of the residuals, the so-called B-model is most commonly used to identify the structural innovations.[11] The B-model assumes that the forecast error components of u_t are linear functions of the underlying independent structural innovations ϵ_t. Normalizing the structural innovations to $\epsilon_t \sim (0, I_n)$, the covariance matrix of the B-model $B\epsilon_t := u_t$ provides the following restrictions:

$$\Sigma_u = B\Sigma_\epsilon B' = BI_nB' = BB'. \tag{5}$$

[10] Lütkepohl (2005) p. 257 et sqq. provides details.

[11] See Lütkepohl (2005), p.369 for further details on the SVAR classification.

Since the $n \times n$ covariance matrix is symmetric, the B-model leaves the researcher with $\frac{1}{2}n(n-1)$ restrictions to specify.[12] Due to the quadratic form, the result will not be unique. For any solution B the matrix $B\Lambda$, with $\Lambda = diag(i_1, .., i_n)$, $i \in \{-1, 1\}$, will also be a solution since $B\Lambda\Lambda' B' = Bdiag(i_1^2, .., i_n^2)B' = BI_nB' = BB'$.

As shown above the VECM has the following MA representation:

$$y_t = \Xi B \sum_{i=1}^{t} \epsilon_i + \sum_{j=0}^{\infty} \Xi_j^* B \epsilon_{t-j} + y_0^* \tag{6}$$

where $\Xi = \beta_\perp[\alpha'_\perp(I_n - \sum_{i=1}^{p-1}\Gamma_i)\beta_\perp]^{-1}\alpha'_\perp$, $\sum_{j=0}^{\infty}\Xi_j^* B\epsilon_{t-j}$ is an I(0) process and y_0^* contains initial values. All long-run effects must be contained in the common trends term $\Xi B \sum_{i=1}^{t}\epsilon_i$, since the Ξ_j^* are absolutely summable and therefore they must converge to zero as j approaches infinity. The $n \times n$ matrix ΞB has rank $n - r$, i.e. at most r rows can be linearly dependent. Thus, at most r of the structural innovations can have transitory effects, since ΞB cannot contain more than r rows of zeros. Therefore, the remaining $n - r$ structural innovation must have permanent effects.

The matrix $\Xi = \beta_\perp[\alpha'_\perp(I_n - \sum_{i=1}^{p-1}\Gamma_i)\beta_\perp]^{-1}\alpha'_\perp$ can then be estimated with standard maximum likelihood estimation. Given the $\tilde{\Xi}$ estimate, the maximum likelihood estimator of $\tilde{B}$ can be computed using the assumed restrictions.

2 The Baseline Model

The number of restrictions necessary for identification impose the trade-off in SVARs between the number of included variables and the number of necessary assumptions which increase quadratically with the former. With this in mind, the law of decreasing credibility stated by Manski (2007), serves as a boundary to excessive assumptions. It states that the credibility of a result is monotonically decreasing in the number and severity of the assumptions, which were necessary to achieve it. Consequently, the computed SVARs reported here will be restricted to a small number of variables, generally less than six. To allow comparability, I will rely on the identification strategy laid out in Beaudry and Lucke (2009) as the baseline model. Therefore, I will start by presenting the baseline model and then depart into different variations of the included variables.

The baseline model uses as variables TFP, the relative price of investment goods, a stock market index, hours and the federal funds rate. Consequently, an identification

[12] A $n \times n$ matrix contains n^2 values. Assuming symmetry leaves the diagonal with n values and half of the remaining values $\frac{n^2-n}{2}$ for specification. The equation above contains n linear restrictions, hence there are $n + \frac{n^2-n}{2} - n = \frac{n(n-1)}{2}$ values to specify.

needs to impose at least $\frac{1}{2}n(n-1) = 10$ restrictions on the short and long-run matrices. Beaudry and Lucke propose the following connections between these variables and structural innovations: TFP should contain information on disembodied technology; the relative price of investment is supposed to indicate investment specific technology shocks; a stock market index helps to identify news shocks; the federal funds rate serves as an indicator of monetary policy shocks while hours are included as a measure of economic activity.[13]

2.1 Identification

Recalling the VECM MA representation, the long-run effects are contained in the matrix ΞB, where B is the short-run impact matrix. In contrast to recursive VARs which rely on the Cholesky decomposition, the structural identification does not depend on the ordering of variables. The non-restrictive ordering of the endogenous variables can therefore be assumed to be as follows: TFP, inverse relative price of investment, stock price index, hours and federal funds rate. The structural innovations are then ordered according to the given identification above. The following assumptions can be utilized to identify the shocks:

Assumption A: Only TFP shocks may have contemporaneous effects on TFP, that is: $[B]_{12} = [B]_{13} = [B]_{14} = [B]_{15} = 0$. In addition preference shocks and monetary shocks have no long-run effect on TFP, i.e. $[\Xi B]_{14} = [\Xi B]_{15} = 0$. Furthermore, monetary shocks have no instant effect on economic activity, that is: $[B]_{45} = 0$.

Assumption A identifies the structural disembodied technology shock to be the unpredictable residual component of TFP, which is assumed to be independent of the other structural shocks. This assumption is a manifestation of the common belief of TFP shocks driving business cycle fluctuations and it additionally prevents news shocks from affecting TFP on impact, since at the time of arrival the news innovation is by definition an unanticipated shock without restricting its long-run effects. The short-run neutrality of investment specific technology shocks (IST) is derived from the assumption of independent TFP innovations in the literature.[14] The long and short-run neutrality restrictions of preference and monetary policy shocks are in line with common beliefs on the effects of these shocks. The assumption of no contemporaneous effect of monetary policy on economic activity is commonly employed as the identifying assumption in the monetary policy literature, e.g. Christiano, Eichenbaum, Evans (1996) while others like

[13]Beaudry and Lucke provide in their robustness section evidence that exchanging hours by another measure of economic activity as GDP or investment does not change the resulting dynamics. Threrefore a comparison of the different activity measures here is omitted.

[14]See Fisher (2006) and Greenwood, Hercowitz and Krusell (1997).

McCallum find even a lag of one quarter questionable though defensible.[15]

$$B_A := \begin{bmatrix} * & 0 & 0 & 0 & 0 \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & 0 \\ * & * & * & * & * \end{bmatrix} \qquad \Xi B_A := \begin{bmatrix} * & * & * & 0 & 0 \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \end{bmatrix},$$

Assumption $\mathbf{B_1}$: News shocks, preference shocks and monetary shocks have no contemporaneous effect on the relative price of investment, i.e. $[B]_{23} = [B]_{24} = [B]_{25} = 0$.

This assumption captures the IST model assumption that only one shock affects the process of investment specific technological change as usually implemented with a linear function that transforms consumption goods into investment goods. Hence, no other shock should matter for this process on impact. Since only three more restrictions are needed, the first restriction on the impact effect of TFP shock is dropped. Nevertheless, robustness checks employed by Beaudry and Lucke find that this overidentifying restriction is not rejected by the data. Furthermore, under the identification scheme A and B_1 the preference shock essentially represents all non-monetary shocks that are orthogonal to technology shocks on impact and have no long-run effects on TFP.

Alternative **Assumption $\mathbf{B_2}$:** Preference shocks and monetary shocks have no long-run effects on the relative price of investment, that is: $[\Xi B]_{24} = [\Xi B]_{25} = 0$. Moreover, it is assumed that IST-shocks have no long-run effect on TFP ($[\Xi B]_{12} = 0$).

In contrast to the former assumption B_1, this set of assumptions relies completely on long-run restrictions. It enriches the set of possible short-run dynamics by allowing contemporaneous effects of all shocks on IST, while restricting the long-run effects on it to zero. Again, the overidentifying restrictions $[\Xi B]_{21} = [\Xi B]_{22} = 0$ are dropped out of the assumption, although at least the TFP shock long-run restriction $[\Xi B]_{21} = 0$ is found not to be rejected by the data.

Chari, Kehoe and McGrattan (2008) subject the SVAR model to a natural test using simulated data of a multiple shock business cycle model. They find that if the number of observations are small, SVARs that rely on long-run restrictions have problems identifying the correct impulse responses if demand shocks play a non-trivial role and the number of shocks is bigger than the number of variables included into the model. Therefore, one might prefer the former identification scheme since it imposes less long-run assumptions. On the other hand, Beaudry and Lucke propose a structural

[15] Clarida, Galí and Gertler (1999) summarizes the literature that found significant short-term effects of monetary policy shocks on real variables. McCallum (1997) p. 357

model that if used as a data generation process, shows that the identification strategy employed here works reasonably well on the simulated data.

While the credibility of the imposed assumptions, deducted from considerations concerning IST theory, is rather high, it exhibits a major obstacle with respect to extending the analysis of news shock dynamics towards other variables just because the IST theory provided so many productive assumptions for the identification process. The quadratic cost in terms of restrictions which are needed to be assumed, deters me from growing the system above five variables, since it would require five extra restrictions which without strong justification would severely decrease the credibility of the results. Subsequently, I will provide another assumption to ease the identification process:

Assumption C: Monetary Policy has no long-run effect on economic activity, that is: $[\Xi B]_{45} = 0$.

The comparison of all the reported impulse responses provides a case for a long-run neutrality, since all identification schemes employed here exhibit that the effect of monetary shocks wears off rather quickly, i.e. in less than eight years and the zero effect lies usually within the computed standard error bootstrapped confidence intervals.[16] So while acknowledging the risks of using short time series together with long-run restrictions, as pointed out by Chari, Kehoe and McGrattan, the addition of other credible assumptions eases the costs of adding another variable into the Structural Vector Error Correction Model significantly. The Appendix provides the FEVDs and IRs for the identification scheme employing assumption C.

2.2 Data

To estimate the SVEC model, I will use quarterly data from a variety of different sources which I will specify further in this section. The common treatment of the variables includes, if applicable, the adjustment for seasonal variation using the X-12 ARIMA algorithm provided by the United States Census Bureau, taking natural logs, normalizing the variables to per capita values by dividing by civilian non-institutional population, ages 16 and over, and expressing them in real values by relying on an applicable deflator.[17] Non-investment related variables are, if applicable, inflation adjusted using the consumption deflator, since consumption represents the ultimate goal of economic activity. All variables and the applied transformations are described in the Appendix.

The National Income and Product Accounts (NIPA) provide data for the seasonal

[16] The one exception is the robustness check employed using only two cointegrating vectors.

[17] A X-12 ARIMA implementation can be obtained from US census bureau at `http://www.census.gov/srd/www/x12a/`.

adjusted time series of non-farm private business GDP, consumption, investment and their respective deflators. Hours worked in the non-farm private business sector are taken from the Bureau of Labor Statistics (BLS) productivity statistics. The capital services data is taken from the BLS Multi Factor Productivity statistics which provides yearly data on a non-farm private business Tornqvist aggregate of capital stocks benchmarked to the productive capital stock in 2000 and contains equipment, structures, inventories and land using rental prices to determine the weights.[18] The capital stock data is interpolated into quarterly data assuming constant quarterly growth rates within years and is adjusted by capacity utilization rates for manufacturing provided by the Federal Reserve.[19] The non-farm private business sector TFP series is constructed using non-farm private business sector data on labor share from the BLS productivity statistics, hours and capital service measures presented above and the usual assumptions of efficient factor markets and a Cobb-Douglas production function with a constant capital share of 31%: [20]

$$lnA_t = lnY_t - \alpha_t lnK_t - (1 - \alpha_t) lnL_t. \tag{7}$$

As a measure of representative stock market movement the standard S&P 500 Index is taken.[21] It represents the broadest widely used measure of US stocks containing 500 of the biggest US companies with respect to market valuation.[22] The inverse relative price of investment goods is determined by dividing the equipment price deflator by the price deflator of non-durables, both taken from the NIPA data. The effective federal funds rate time series is provided by the Federal Reserve. The Appendix delivers details on the data sources, time ranges and transformations of all used variables.

[18]Please see the BLS Handbook of Methods (1997) p.92 et seq. for details on the computation and the definitions employed.

[19]Agreeably the manufacturing sector is less relevant today than it was 40 years ago. Nevertheless the capacity utilization rates in manufacturing are probably still one of the best feasible indicators available if one agrees that manufacturing is still deeply connected with the rest of the private non-farm business sector economy. Beaudry and Portier (2006) emphasizes that in their bivariate SVEC model adjusting for capacity utilization results in dynamics which are very close to the dynamics derived using the TFP series produced by Basu, Fernald and Kimball (2006) which is constructed from disaggregated data.

[20]The use of a Tornqvist index specification with varying capital share does not affect the results qualitatively and is therefore omitted.

[21]The original S&P Index has not been published before 1957. Shiller (2005) uses a variety of available data to construct a longer dataset containing a complete monthly time series beginning in 1871.

[22]Only stocks traded either at the NASDAQ or the NYSE are considered. The valuation of these 500 companies was on the 30. September 2009 approximately 9 trillion dollars representing about 75% of the combined market value of all US traded equities.

In the following, I will describe the choice of parameters in the estimation procedure. Since I want to compare a variety of different systems, I will use in all VECMs the same number of lags. The Akaike Information Criterion recommends the use of five lags in differences, which seems to be a reasonable trade-off between estimation precision and the risk of biased results due to lag truncation. This means that the VECM estimates now contain 155 parameters. In addition, I have to assume the number of cointegrating vectors. The Johansen trace test as well as the Saikkonen & Lütkepohl test as reported in Table 1, reject zero and one cointegrating vector, but do not rule out two or three on the 5% level. Besides, the rejection of zero cointegrating vectors implies that a VECM specification is appropriate.

As Beaudry and Lucke show in their robustness check that estimating two cointegrating vectors seems to lead consistently to permanent effects of monetary policy shocks on economic activity. Since this reaction is not in line with economic theory, I will instead assume three cointegrating vectors. Furthermore, I will allow for a deterministic time-invariant component in the regressions. Estimating the described structural system under the assumptions A and B_1 and simulating impulse responses and FEVDs as presented in Figures 1 and 2, delivers the following results:[23]

While in the short-run, surprise TFP shocks are the most important contributor to the variance in TFP, in the long-run (after eight years), news shocks overtake surprise TFP shocks and continue to rise in importance as can be seen from the Figure 16 in the Appendix. All other shocks exhibit rather small contributions to the variance of TFP, in line with the conjecture that only surprise TFP shocks and news shocks influence TFP.

The IST shocks predominates the variance of the relative price of investment at all horizons which supports the identification of structural IST shocks as an important factor in investment. The news shock is unimportant on near horizons, but has a growing influence for the long-run (around 20% after four years).

In contrast, the contribution of IST shocks as well as surprise TFP shocks to the variance of hours is low at all horizons. While the preference shock is important in the first three quarters, the news shocks are the main driving force of macroeconomic

[23]This estimation coincides with the NIPA_h ID1 system in Beaudry and Lucke

# of cointegrating vectors	0	1	2	3
Johansen Trace Test	0.000	0.001	0.076	0.264
Saikkonen & Lütkepohl Test	0.000	0.003	0.080	0.396

Table 1: p-values for the number of cointegrating vectors

fluctuations in economic activity exhibiting a gradual increase in variance contribution within the first two years and holding that influence afterwards. The response of economic activity to monetary policy shocks is, in line with empirical findings, delayed by around two years and does not contribute more than 15% to the variance of hours.

In line with the structural identification, the interest rate forecast error variance is dominated by the monetary policy shock on all horizons. While the large share of preference shocks signal at least one missing factor in the evolution of interest rates, the increasing importance of surprise IST shocks might reflect the monetary policy reaction to the pressure on the price level that builds over time after an IST shock.

Consistently with the concept of identifying news shocks through stock prices, stock prices are mainly driven by news shocks on all horizons. The diminishing short-run impact of monetary policy shocks on the stock market coincides with the anecdotal evidence of stock market reacting to releases of Federal Open Market Committee minutes or inflation-data which reflect changes in monetary policy.

The associated impulse responses in Figure 2 provide further evidence for news shocks reflecting anticipated technology changes. The impulse response of TFP on a news shock is at most slightly negative within the first three years, but significantly positive afterwards. Furthermore, a positive news shock increases stock prices and produces a hump-shaped response of hours, which is consistent with a technology improvement that needs hours to build and hours being stationary. The effect of news shocks on the relative price of investment goods concurs with such a mechanism, while the positive short-run response of a monetary policy shock on the interest rate is consistent with common findings in the monetary policy literature, as for example Bernanke and Gertler (1995). The lagged positive response of interest rates on a rise in hours coincides as well with conventional wisdom. Moreover does the IST shock exhibit mostly insignificant effects on the other time series and the surprise TFP shock does not have any significant effect on hours, stock prices or the relative price of investment. The hump-shaped increase in TFP, as a reaction on a monetary policy shock, might be explained by a layoff-effect on TFP, because the increase in interest rates reduces hours worked, increases unemployment and therefore, assuming decreasing marginal productivity, increases measured labor productivity. If one compares the impulse responses of hours and TFP on a monetary shock, one can see the nearly perfectly mirrored responses.

Using the identification system $\mathrm{A}B_2$ instead which relies more heavily on long-run restrictions, does not change the main results. This result is not surprising, since the identified shocks are highly correlated with the shocks from the identification scheme $\mathrm{A}B_1$. For this reason the corresponding FEVDs and IRs are deferred to the Appendix (Figures 20 and 21).

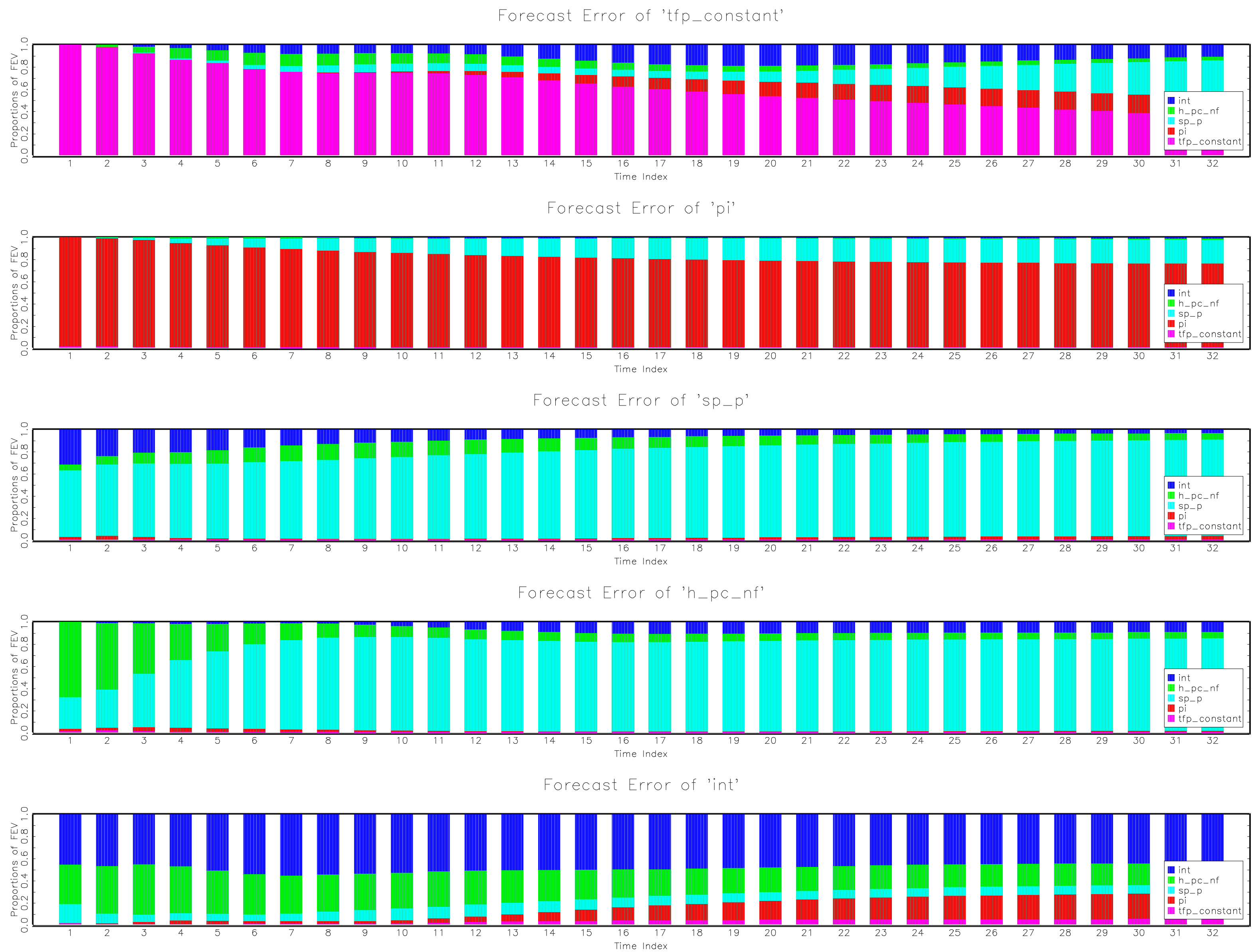

Figure 1: FEVDs of identification AB_1 with TFP constructed using a constant labor share, 1955Q1-2008Q4

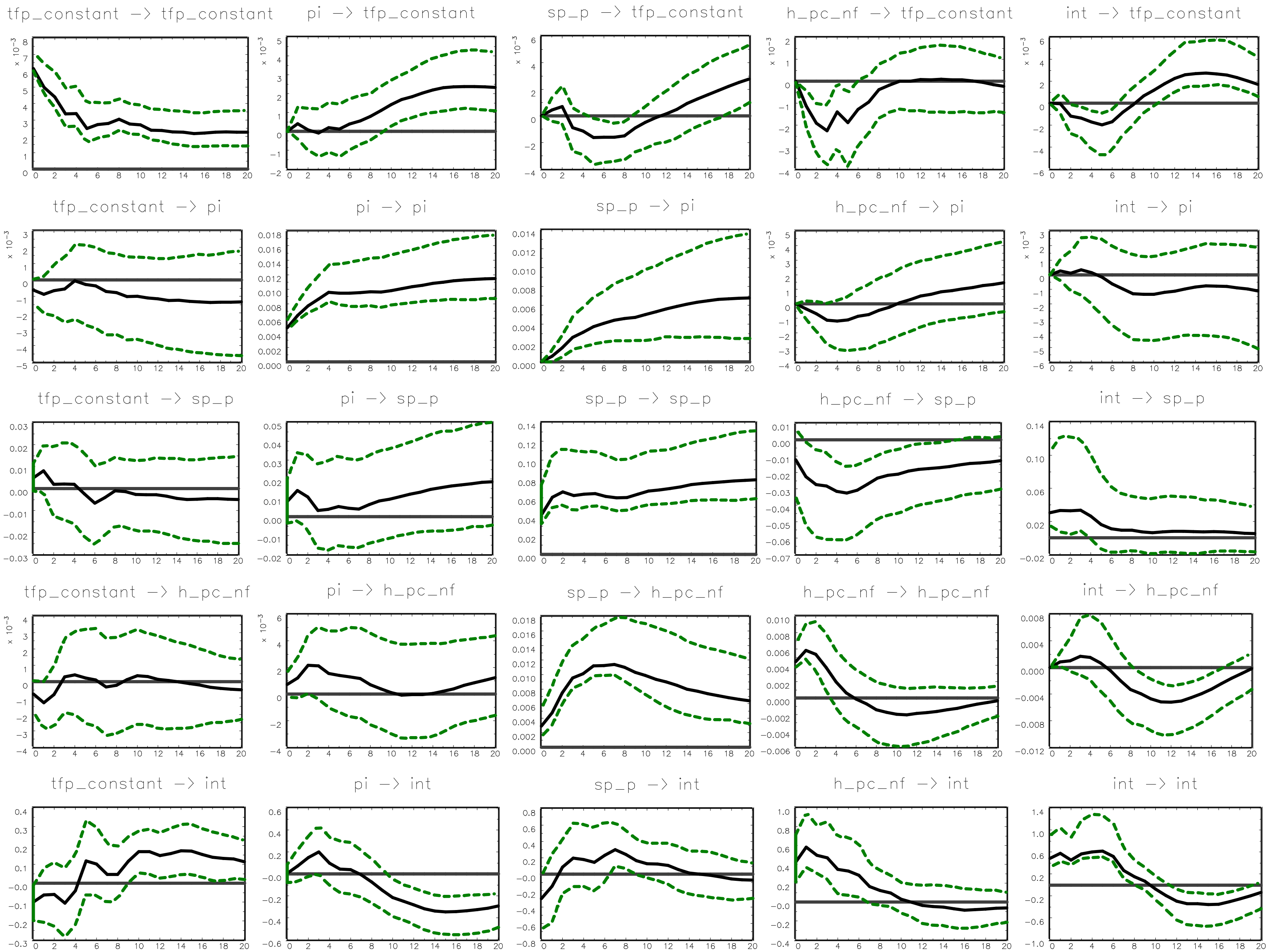

Figure 2: IRs of identification AB_1 with TFP constructed using a constant labor share, 1955Q1-2008Q4, dashed lines represent 95% bootstrapped Hall confidence intervals.

2.3 Dropping the IST shock

Using the baseline system explored above, I want to analyze and compare a variety of different time series concerning their impact on the news shock dynamics. Since the IST shock has proven to be rather disconnected to the rest of the variables in the system, I will replace the inverse relative price of investment variable by other variables of interest. For the sake of comparability, I will provide in the following the FEVDs and IRs for the four-variable system without IST shocks. The identification relies again on the assumption A which provides now six restrictions.[24] The identification scheme now looks as follows:

$$B := \begin{bmatrix} * & 0 & 0 & 0 \\ * & * & * & * \\ * & * & * & 0 \\ * & * & * & * \end{bmatrix} \qquad \Xi B := \begin{bmatrix} * & * & 0 & 0 \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{bmatrix},$$

where stars denote unrestricted entries. In a four-variable system only $\frac{1}{2} * 4 * (4-1)$ restrictions are needed. Hence, the six restrictions provided by assumption A are sufficient to identify the structural shocks. The Johansen trace test still supports three cointegrating vectors with a p-value of 0.543, while the p-value of two cointegrating vectors declines to 0.054. Therefore it is justified to continue to assume three cointegrating relationships. As the Figures 5 and 6 show, the results do not change much. The most notable change is the increased contribution of the preference shock to all four FEVDs which is not surprising in the sense that the interpretation of the preference shock was given above as a collection of excluded shocks.

3 The Nature of News Shocks

In the following, I will explore a variety of different time series to understand the nature of a news shock. The starting point of all branches is the baseline system laid out above. I will deviate from the system either by substitution of the IST shock in the five-variable system or by substituting the news shock in the four-variable system. Since the ultimate aim of this analysis is to gain some insight in the composition and nature of news shocks, I will explore at first possible alternative measures of equity prices.

[24] The unmodified assumption A included the restriction that IST shocks have no impact effect on TFP which is dropped in four-variable system.

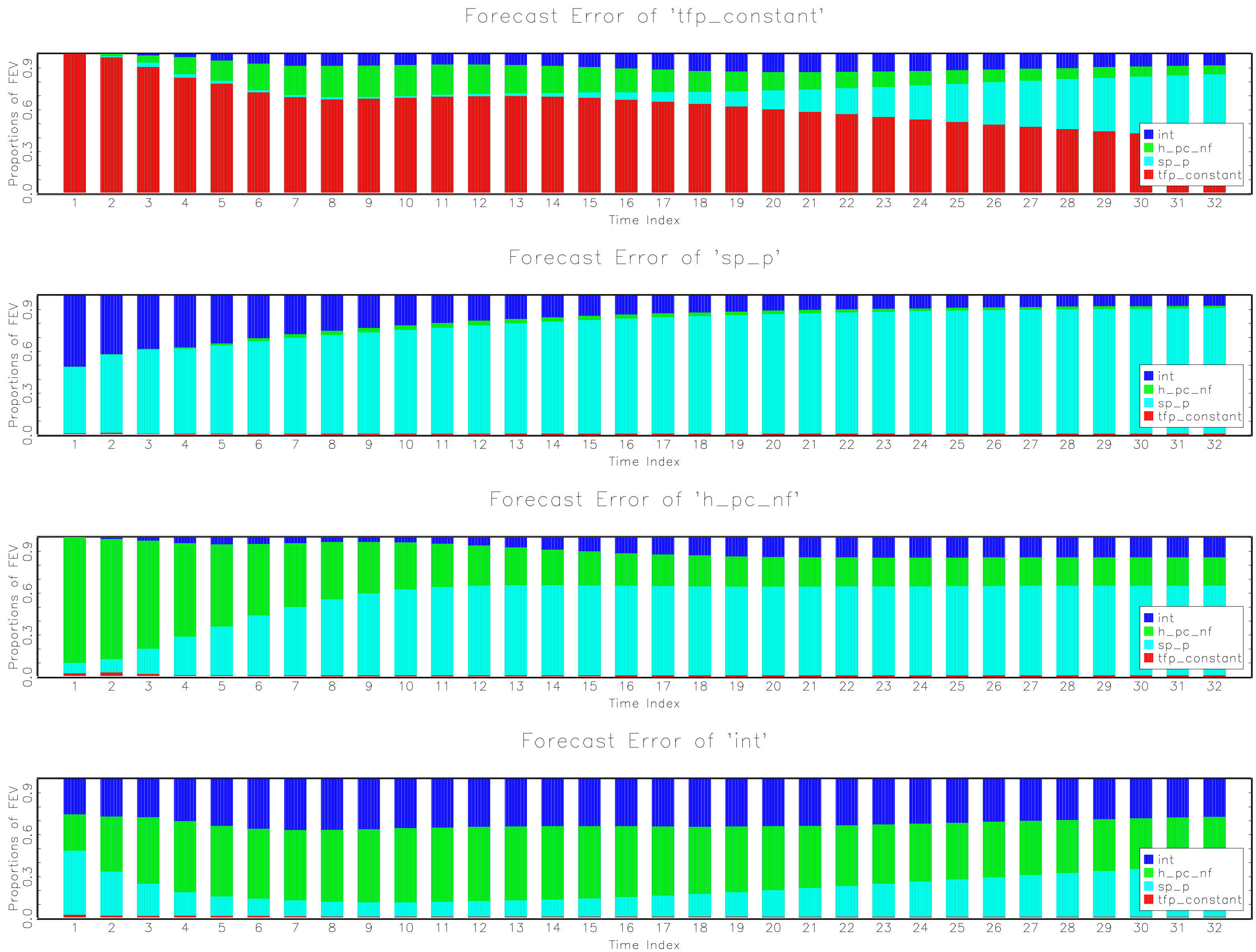

Figure 3: FEVDs of identification A with TFP constructed using a constant labor share, 1955Q1-2008Q4

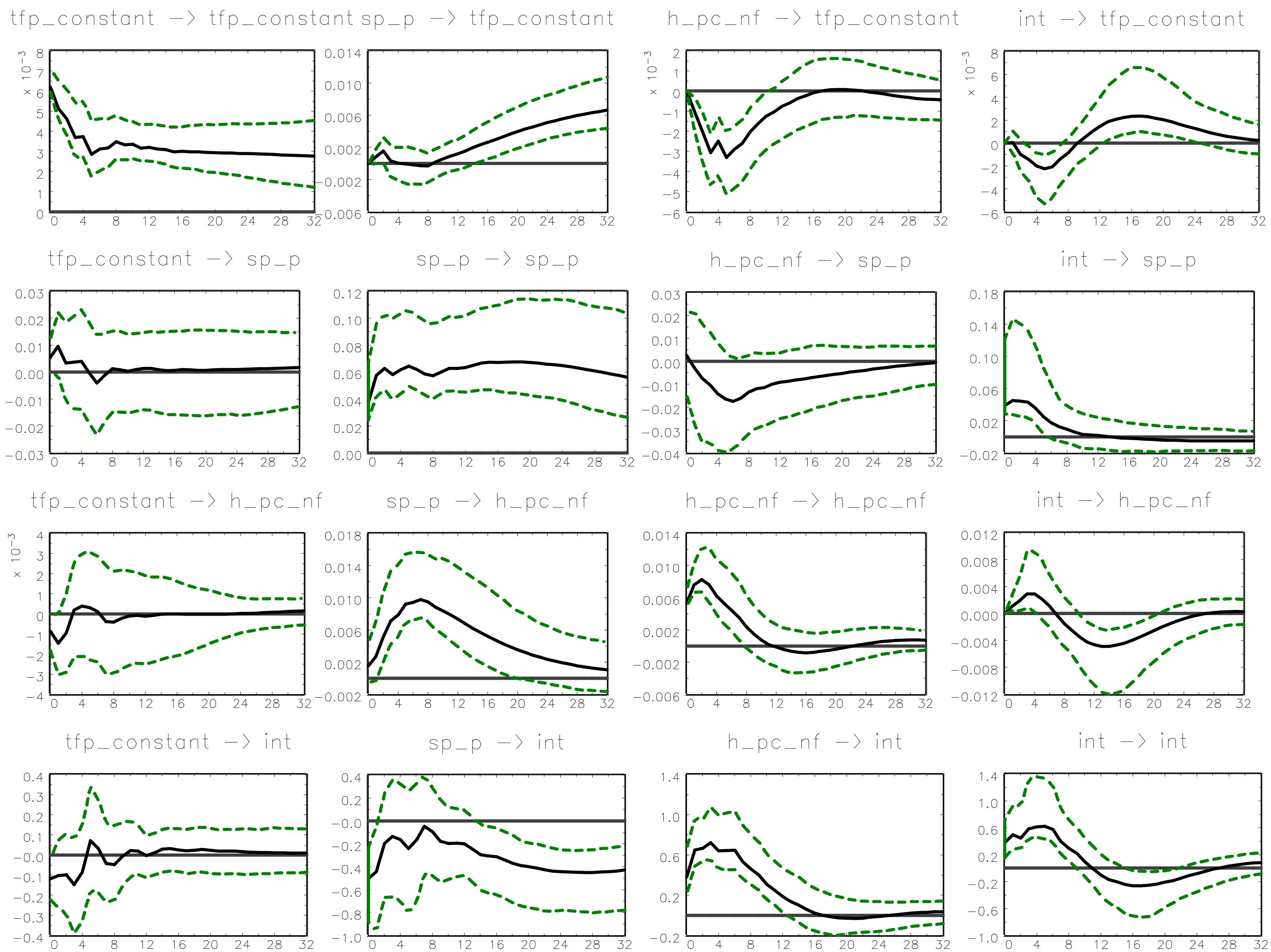

Figure 4: IRs of identification A with TFP constructed using a constant labor share, 1955Q1-2008Q4, dashed lines represent 95% bootstrapped Hall confidence intervals.

3.1 Equity Shares Prices

Equity constitutes the most committed share of working capital for any given company. It serves as a risk buffer for the remaining capital needed, usually supplied in some form of debt like bonds, commercial papers and overnight credit-lines. In return, it entitles the holder to any residual profits once all other obligations are fulfilled. This is the source of the interpretation of news shocks as anticipated technology shocks. The asset pricing theory determines the value of the equity by calculating the present value of all future profits net of all obligations. The efficient market hypothesis (EMH) then implies that an anticipated technology shock should change the current valuation of equities that are affected by the shock, since their profit prospects change. Since technology shocks are unlikely to affect any sector of the economy equally, one favors the broadest available measure of equities. Although the S&P 500 index includes approximately 75% of the joint market capitalization of all publicly traded companies, it focuses on large companies which makes it by definition a skewed measure of equity prices. Accordingly, the first variation adds a broader stock market index, the Wilshire 5000 Total Market Index. This index is composed of all publicly traded U.S. companies and weights them by market value.[25] The Johansen trace test rejects a cointegration rank of three on a 5%-level, but not on a 1%-level (p-value 0.015).[26] For the sake of comparability, I will therefore use three cointegrating vectors. Employing the identification scheme AC, one needs to impose two more restrictions to just identify the structural system. By definition,the Wilshire 5000 contains all shares that are indexed in the S&P 500. Besides, their relative weights coincide to their weights in the S&P 500. Consequently, the following restriction may be justified: The narrow news shock, as identified using the S&P 500, does not effect the Wilshire 5000 neither in the long- nor in the short-run. Hence, this assumption which will be referred to assumption D, identifies the contribution of changes in the valuation of large companies to business cycle fluctuations. The

[25] By definition the composition of this index changes whenever a company is taken private, goes bankrupt or issues publicly traded shares for the first time (IPO). Currently there are approximately 6300 stocks in the index.

[26] The hypothesis of two cointegrating vectors can be rejected on a 1%-level (p-value 0.001) while the hypothesis of four cointegrating vectors can not be rejected on a 5%-level (p-value 0.085). Additionally do four cointegrating vectors lead to a singular SVECM estimation matrix given the provided identification.

identification scheme then looks as follows:

$$B := \begin{bmatrix} * & 0 & 0 & 0 & 0 \\ * & * & 0 & * & * \\ * & * & * & * & * \\ * & * & * & * & 0 \\ * & * & * & * & * \end{bmatrix} \qquad \Xi B := \begin{bmatrix} * & * & * & 0 & 0 \\ * & * & 0 & * & * \\ * & * & * & * & * \\ * & * & * & * & 0 \\ * & * & * & * & * \end{bmatrix}.$$

The dynamics in Figure **??** and **??** provide a strong indicator that using a broader index than the S&P 500 provides valuable information on the news shock. To distinguish the two news shocks in the system, I will in the following use the term 'broad news shock' for the news shock associated to the Wilshire 5000 and 'narrow news shock' in reference to the original S&P 500 news shock.

The long-run TFP variance is dominated by the broad news shock, while the narrow news shock is only of minor importance at all horizons. In contrast to the broad news shock, the narrow one has a consistently bigger short-run effect on TFP, economic activity and interest rates. Conversely to this finding, both measures of equity prices are strongly dominated by the broad news shock contributing about 95% to both variances on all horizons, while the narrow news shock provides at most 3% to both. Following the interpretation of the preference shock as a measure of all excluded shocks, the FEVDs show that the broad and narrow news shocks together do capture nearly all otherwise excluded shocks. Interestingly, the broad news shock mimics the behavior of gradual increasing contributions to the variance of economic activity. This behavior has been attributed to the narrow news shock in the baseline model. In contrast, the narrow news shock contributes now most of the remaining variance with a higher impact in the short-run (around 90%). While the narrow news shock had only a minor influence on the variance of interest rates, this changes in the presence of a broader news shocks. Similarly to its gradual increasing influence on hours and TFP, the broad news shock only affects interest rates on far horizons. Comparing the impulse responses to the benchmark case reveals that the broad news shock now causes the same responses attributed before to the narrow one, most importantly regarding the long-run effect on TFP. Besides its effect on the interest rates, the narrow news shock dynamics resemble the broad news shock's dynamics while mostly being insignificant.[27] Furthermore, the preference shock is now barely relevant, which indicates that the most important shocks are now included in the system.

I conclude that in the presence of the broader index, the S&P 500 index loses its long-run importance and gets reduced to a short-run impact on economic activity and TFP,

[27]If one instead uses a Tornqvist specification TFP measure the contributions to the variance of stock market indices distributes over all horizons more equally to all five shocks but does not change the impact of the broad news shock on the other variables.

while still contributing to the variance of interest rates in the long-run. The importance of the narrow news shock for the variance of interest rates can be rationalized in a model where central banks are limited in their information processing capacities and therefore restrict themselves to indicators that are important in predicting short-run business cycle fluctuations.

These results justify a deeper look into the differences between the S&P 500 and the Wilshire 5000.[28] The most apparent difference is the distribution on market capitalizations. Table 2 and 3 provide summary statistics on the distributions and weights of the components of both indices.[29]

Index	Total MC	Avg. MC	Median MC	Max. MC	Min. MC
S&P 500	$9.32 * 10^{12}$	$18.6 * 10^{9}$	$7.98 * 10^{9}$	$329.8 * 10^{9}$	$814 * 10^{6}$
Wilshire 5000	$12.6 * 10^{12}$	$2.0 * 10^{9}$	$233.9 * 10^{6}$	$329.8 * 10^{9}$	$< 1 * 10^{6}$

Table 2: Summary Statistics, all market capitalizations (MC) in U.S. Dollars

The tables show that the S&P 500 provides a highly skewed measure of equity prices. The advantage of this measure mainly relies in its higher liquidity and lower information costs. The overall share of market transactions focusses heavily on the Top 500. While large companies employ their own investor relations units and have to publish quarterly earnings reports as a requirement for admission into a prime index, small companies mostly do not publish as much data on their business. Furthermore, they differ in their financing methods and their organizational structure. Most smaller companies do not have immediate access to the bond market due to transaction costs. In addition, they are mostly run by managers who have a considerable stake in the company – a strategy that lessens the principal-agent problem. Given the interpretation of news shocks as anticipated technology shocks, one might be inclined to infer from the long-run dominance of the broad news shock over the narrow one, that small companies are more heavily exposed to changes in available technology.

[28] One could substitute the Wilshire 5000 by its subindex, the Wilshire4500 which contains all equities not included in S&P 500, but that would come at the cost of losing the two identifying assumptions used here.

[29] The company with a valuation above 50 billion dollar that is not included in the S&P 500 but in the Wilshire 5000 is Berkshire Hathaway, which does not satisfy the liquidity condition for admission into the S&P 500. The data was last updated in 09/30/2009 and can be found at `http://www.wilshire.com/Indexes/Broad/Wilshire5000/Characteristics.html`, `http://www2.standardandpoors.com/portalsite/sp/en/us/page.topic/indices_500` and `http://www.djindexes.com/mdsidx/downloads/US_BestChoice.pdf` [Last accessed: 10/01/09]

	Market-Cap Ranges in Billion U.S. Dollars							
Index	>50	10-50	5-10	2-5	1-2	0.5-1	0.05-0.5	<0.05
S&P 500	45	185	137	103	29	1	-	-
as % of total MC	50.35	35.88	9.70	3.63	0.43	0.01	-	-
Wilshire 5000	46	196	180	409	486	649	1998	1278
as % of total MC	39.43	29.48	9.46	9.62	5.23	3.49	3.11	0.18

Table 3: Distribution of market caps, Data as of 12/31/2003

3.2 The Relative Price of Investment

Another variables deemed important in the literature is the relative price of investment as a measure of technological progress embodied in capital goods. Fisher (2003) and (2006) finds that the majority of the forecast error variance explained by technology is driven by investment specific technology shocks. This long-run importance of investment specific technology (IST) shocks, which cause changes of the relative price of investment compared to the price of non-durables, has been pointed out earlier by Greenwood, Hercowitz and Krusell (1997), who suggested that it could be important in the short-run as well.

The idea of a news shock suggests a causal reaction of anticipated changes of productivity that at the time of the announcement should immediately affect the demand of capital by optimizing firms. These results can be validated in the present identification scheme A. Substituting the stock price index by the relative price of investment delivers results that are very similar to the results for news shocks. The IST shock has a significant positive effect on productivity after 16 quarters and causes a significant hump shaped response of economic activity, measured in hours, in the same time frame in the impulse responses. While the TFP shock dominates all horizons of the FEVD of TFP it seems rather unimportant for the other time series included. The IST shock, identified through the relative price of investment, predominates the price of investment and has an increasing effect on economic activity measured in hours that reaches its peak after 8 quarters. At the same time the IST shocks seems to be rather unimportant for monetary policy on all horizons. Overall the IST shock behaves very closely to the news shock. As shown by Beaudry and Lucke (2009) in the presence of both in a single SVAR the IST shock becomes unimportant and the news shock dominates. This behavior is consistent with the SVAR theory if and only if the news shock is causal for changes in the relative price of investment identified here as IST shock.

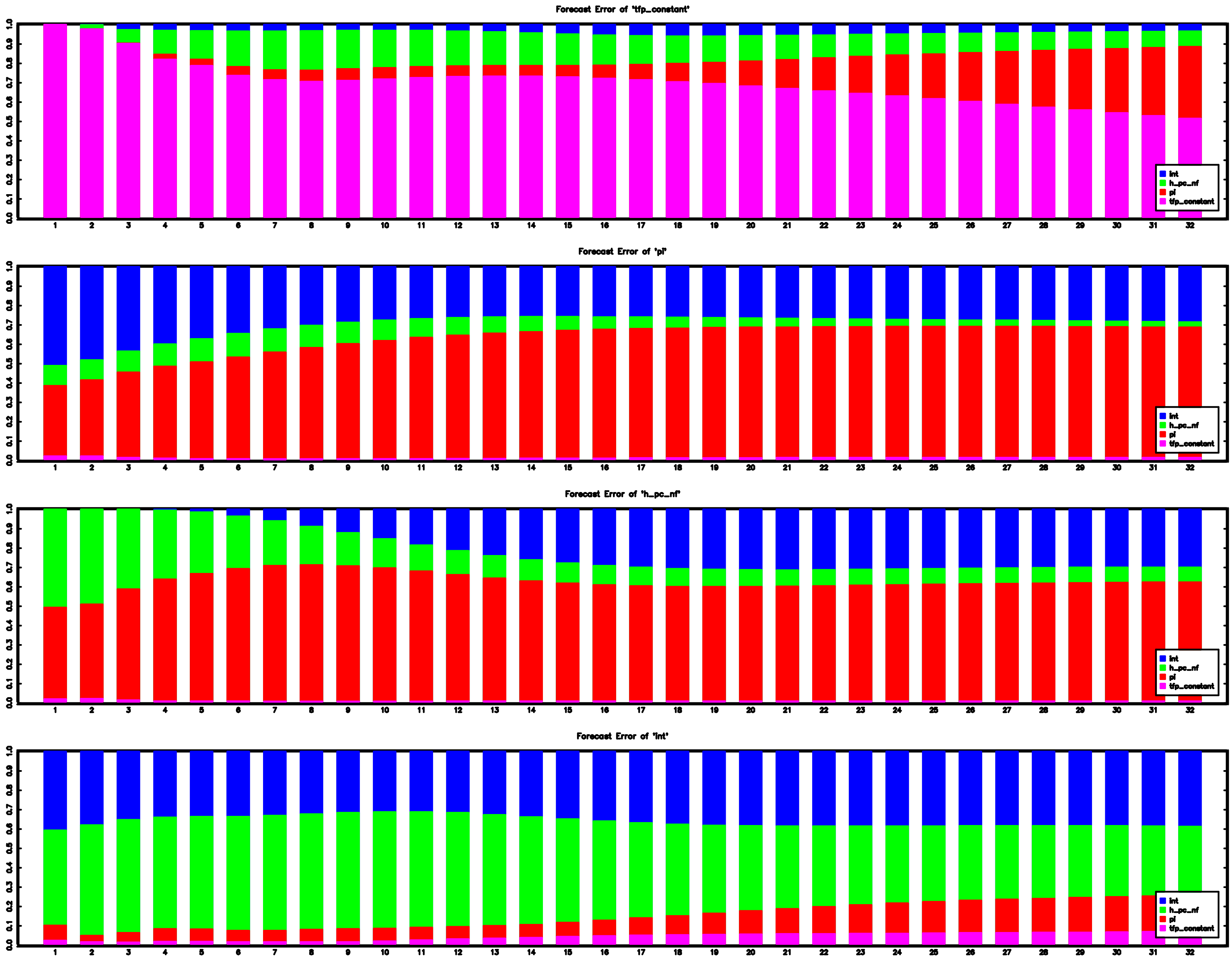

Figure 5: FEVDs of identification A with the relative price of Investment, 1955Q1-2008Q4

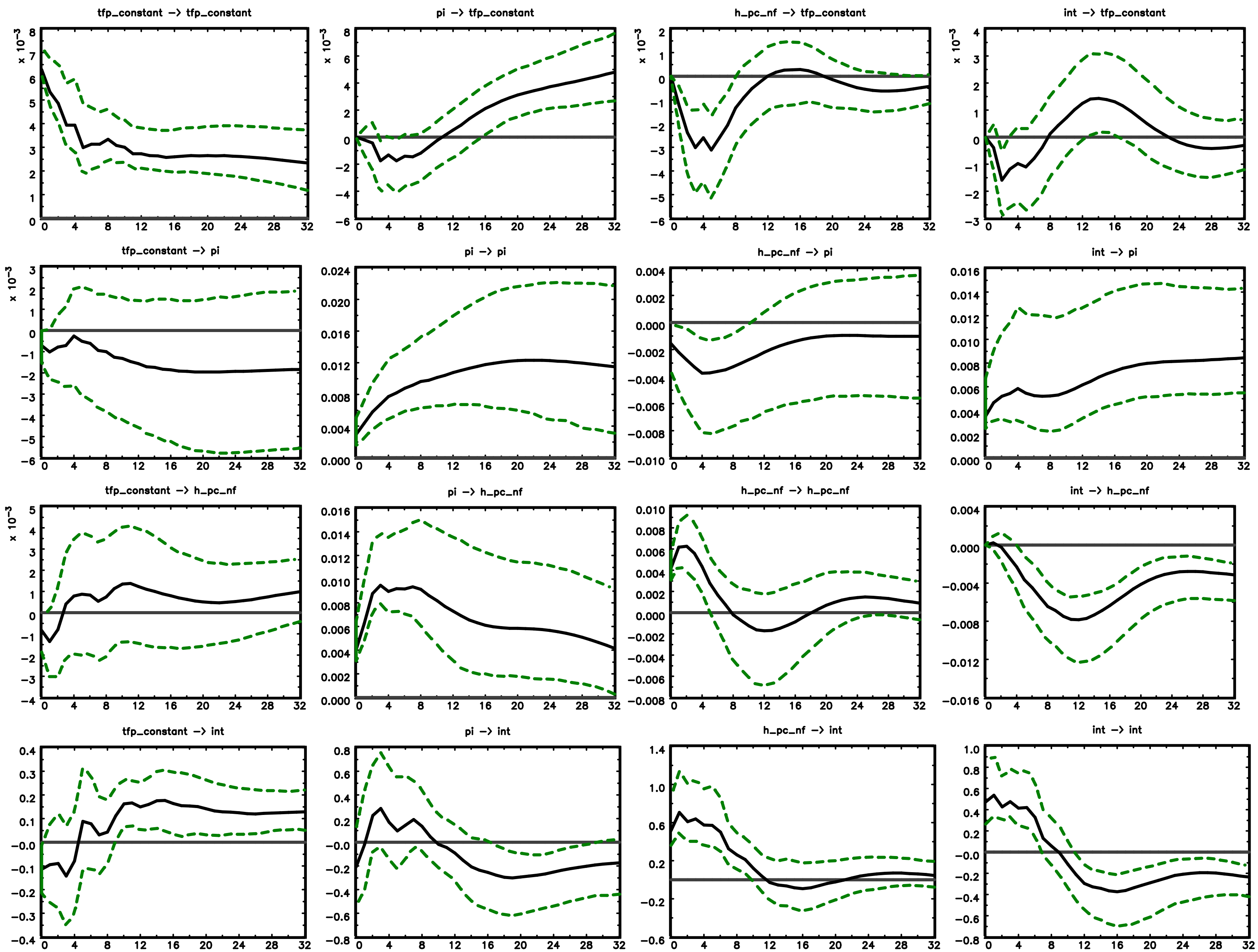

Figure 6: IRs of identification A with the relative price of Investment, 1955Q1-2008Q4, dashed lines represent 95% bootstrapped Hall confidence intervals.

3.3 Patents

Ultimately, an interpretation of a news shock as an anticipated technology shock requires a technological component. Moreover, since competitive markets would lead to immediate imitation of a new technology, the innovator has a strong incentive to protect his innovation, allowing him to capture all rents associated to it. Therefore, the number of patent applications is a relevant measure of technological innovation, while at the same time less quick than forward looking variables, since it takes time to innovate and subsequently, prepare a patent application.

Unfortunately, there are several measurement problems attached. First of all, although the main research might be done the moment a patent application is filed, it may take some time till it is granted.[30] Secondly, I do not have quarterly, but only yearly data which are interpolated assuming constant growth rates. This means that a patent shock needs on average two more quarters to be detected. While real treasuries returns and stock prices are heavily forward looking variables, there is not much reason to believe the same for the number of patent applications. The data set was provided by the U.S. Patent and Trademark Office and only utility patents with U.S. origin are considered. I will again use assumption A and restrict the SVECM to a four-variable system.

Figures 7 and 8 show the following results: A surprise TFP shock affects TFP in the short-run, but its impact decreases after 15 quarters. In addition it has no significant effect on other variables. The patent shock explains an increasing share of TFP variance in the long-run, but contributes nothing to the first 15 quarters. Patents are predominantly explained by the patent shock. The monetary shock impact on patents is decreasing and negligible in the long-run. Hours are in the first four quarters dominated by preference shocks, but after then, mostly patent shocks contribute to the variance of this economic activity measure. Interest rate forecast errors are dominated by preference shocks, while monetary and patent shocks explain equally much variance (around 12% each). By and large, the impulse responses are very close to the four-variable baseline system. Patent shocks have a significant positive long-run effect on productivity after 15 quarters and result in increases of economic activity which reach their peak after seven quarters. All things considered, one can conclude that patent shock mostly induces the same dynamics as the news shocks. Given the predominant technological content of utility patent applications, this result favors a technological interpretation of news shocks.

[30] Using patents granted instead contaminates the data with variances in the evaluation range and Patent Office productivity.

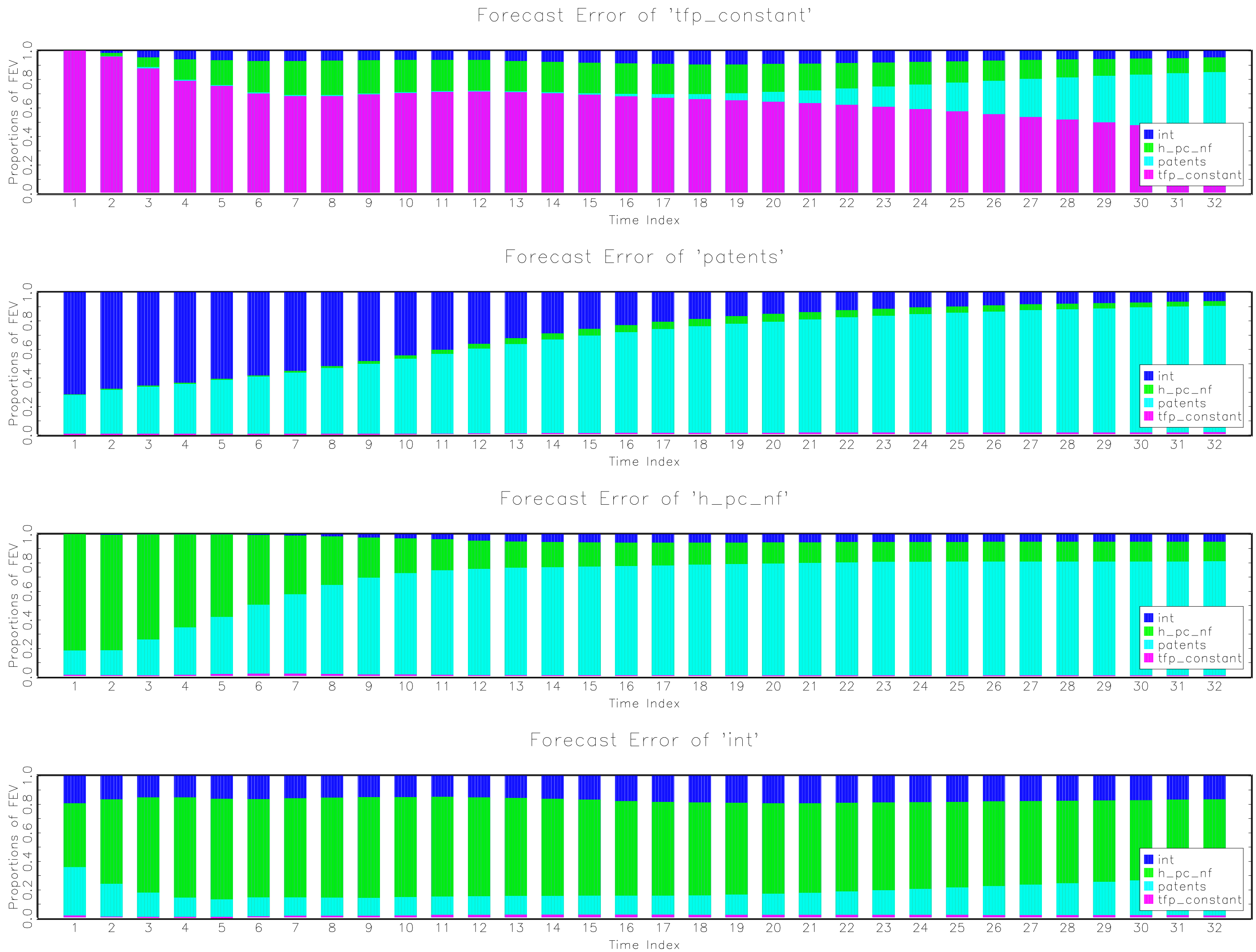

Figure 7: FEVDs of identification A with patents, 1963Q1-2008Q4

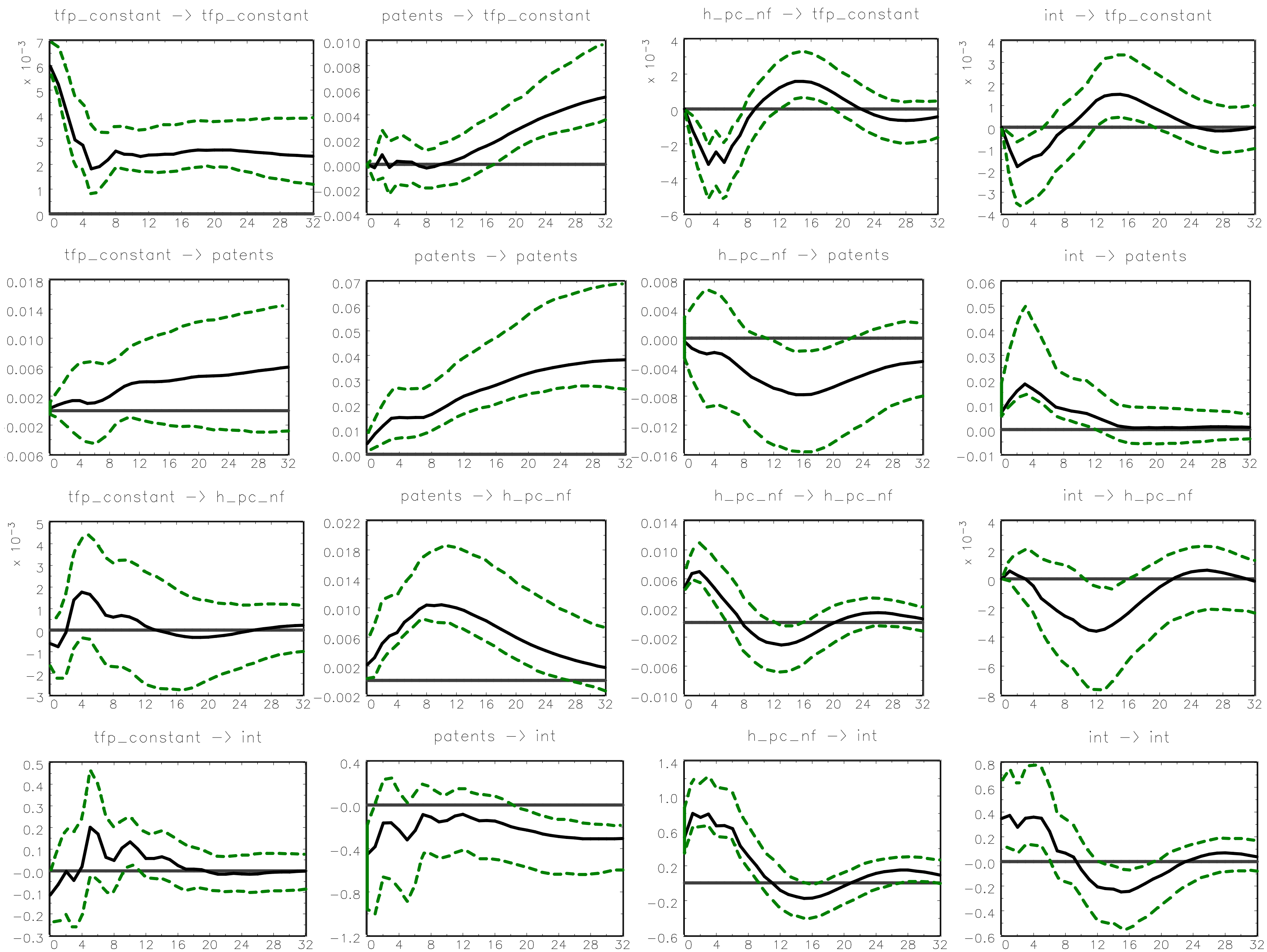

Figure 8: IRs of identification A with patents, 1963Q1-2008Q4, dashed lines represent 95% bootstrapped Hall confidence intervals.

3.4 Fixed-Income Prices

Fixed income assets or bonds offer a guaranteed interest rate payment (coupon) and the repay of the principal at a certain date (maturity). These assets are less risky than equities in the sense, that they provide first-in-line access to the firm's assets in the case of bankruptcy and do not profit from positive developments of the firm's prospects. So why should these assets be effected at all from changes of future profit prospects? Legally they constitute a fixed contract that does not condition on the level of future profits. Instead the second-hand market for these assets gets affected in two ways: First of all, it changes the risk of bankruptcy for any given firm and secondly, it changes the outside option for bond holders and therefore affects the price of these assets. The fundamental motivation for this argument relies on the Modigliani Miller Theorem by which, if one assumes efficient markets, companies should not be able to increase their value by changing their liability structure.

The submarket of the United States government debt (treasuries) is especially relevant, since it is sufficiently deep to absorb nearly any order, therefore it can be assumed to be free of liquidity risk. Furthermore, the U.S. treasuries carry no idiosyncratic default risk.[31] Figure 9 shows how closely the 3-month treasuries follow the effective federal funds rate, which I identified as a source of monetary policy shocks. Therefore, these short-term treasuries will not help much at face value in understanding the news shock dynamics and I will pass on reporting the associated FEVDs and IRs. Moreover, the figure shows how fast monetary policy shocks affect the effective capital cost of companies: The prime lending rate refers to the short-term interest rate, creditors with high credibility are charged with on average across banks. One can conclude that the prime lending rate essentially represents a nearly fixed markup on the overnight federal funds rate, where the markup represents the lower liquidity and the higher default risk.

If the anticipated technology shock interpretation of news shocks is true, it seems reasonable that the effects of productivity changes should be detectible in long-term interest rates as well. Economic theory suggests that long-term interest rates should be calculated based on the net effect of expected future productivity growth, inflation and the costs of delaying consumption. Financial market participants spend a considerable share of their time on forming expectations about future inflation rates, since these are essential in pricing assets. For this reason, I will assume in the following that these agents are able to perfectly forecast future inflation rates. If one assumes further that

[31] Since government activities are deeply interconnected to a variety of important sectors, a government default immediately leads to a chain-reaction of defaults of its counterparties, including every large bank. In this case, it is nearly irrelevant whose bond one holds. Hence, in this sense, one can interpret the market rates on treasuries as the closest measure available to the theoretical construct of a risk free rate.

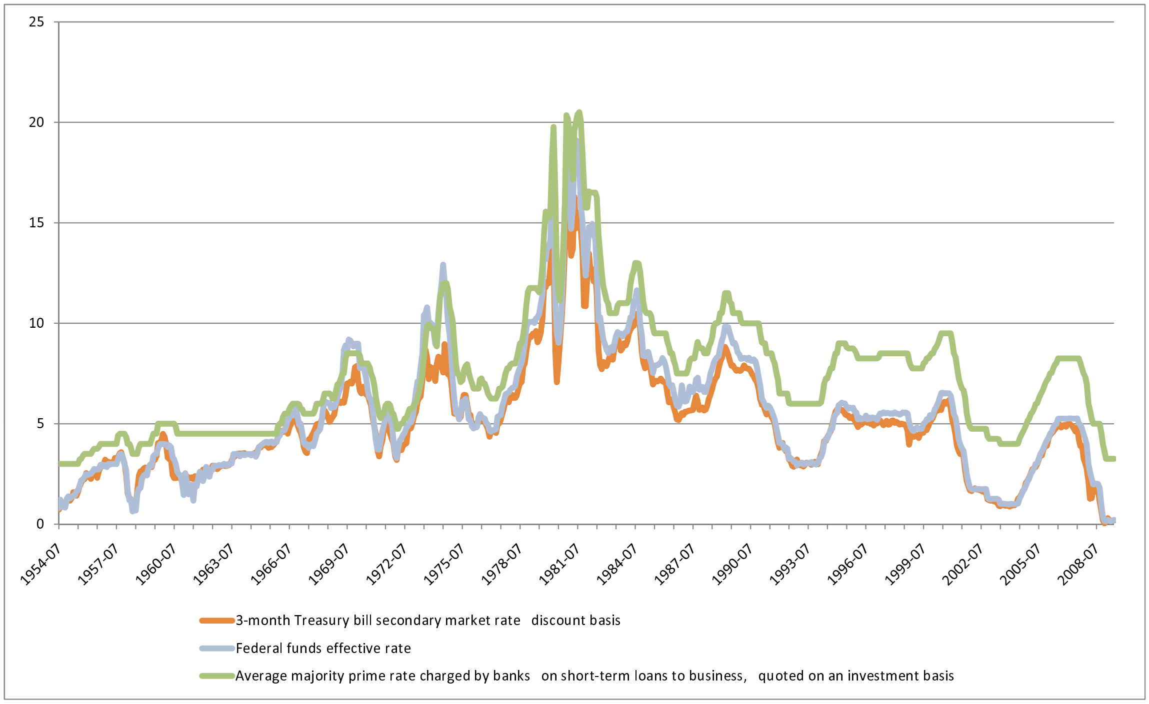

Figure 9: Monthly interest rate measures in percent per year, 1954-2008

the discount rate for future consumption is time-independent, it follows that changes in real long-term interest rates should solely depend on anticipated technology change. While it is hard to decompose long-term prices of bonds into its components, e.g. productivity growth, inflation and default risk, it is easier if one relies on the assumption of rational expectations and uses treasuries as virtual risk-free bonds. I construct a measure of anticipated technology change by subtracting realized inflation between issue date and maturity from the market interest rate for treasuries at the time they were issued. Given the stated assumptions, it follows that if news shocks represent anticipated future movements of productivity, then they must have an impact on the prices of the treasuries, too. Using again assumption A and substituting the stock price index by the described real treasury return, the results for 3-month, 3-year, 5-year and 10-year treasuries are as follows:[32]

Figures 10 and 11 show that surprise TFP shocks are unimportant for economic activity, interest rates and treasuries in the presence of real returns of treasuries. They only matter in the short-run for TFP. The treasury news shock dominates in the long-run economic activity and interest rates. As the news shock, identified through stock prices, does this shock affect the variance of hours in gradually increasing manner within

[32]The Akaike Information Criterion favors again six lags, giving no reason to change the parameter. The cointegration rank is assumed again to be three since the Johansen trace test does not reject the hypothesis for any of the four-variable system described here.

the first 15 quarters. In addition, it always causes a hump shaped response of economic activity that takes around 15 quarters to reach its peak. Furthermore, it almost always leads to a significant long-run increase in productivity, the only exception being the long-run impulse response for the 3-year-treasuries, where it becomes insignificant after 50 quarters.[33] The major discrepancy from the earlier presented FEVDs of the baseline system lies in the bigger impact of monetary policy shocks on the real return of treasuries. This importance of monetary policy shocks is consistent with the view that monetary policy shocks occur more often than anticipated technology changes, which is not surprising given that the FOMC meets at least eight times a year and bond prices being heavily dependent on the current interest rate. Nevertheless, the negligible contribution of surprise TFP shocks and preference shocks to the real return of treasuries supports the identification scheme. Given the assumptions portrayed above, one can conclude that the real treasuries return shock must be predominantly technological. All things considered these responses are very close to the baseline four variable system with a stock market news shock, hence it seems reasonable to infer that their dynamics are caused by a common shock.[34]

Correlations	S&P500	Wilshire5000	pi	Patents	T_3m	T_3y	T_5y	T_10y
S&P500	1,00	0,94	0,83	0,06	-0,19	-0,27	-0,55	0,73
Wilshire5000	-	1,00	0,94	0,08	0,09	0,08	-0,01	0,97
pi	-	-	1,00	0,98	0,16	0,12	0,18	0,25
Patents	-	-	-	1,00	-0,01	0,68	0,70	0,62
r_int_3m	-	-	-	-	1,00	0,78	0,73	0,58
r_int_3y	-	-	-	-	-	1,00	0,96	0,86
r_int_5y	-	-	-	-	-	-	1,00	0,93
r_int_10y	-	-	-	-	-	-	-	1,00

Table 4: Correlations

A concern raised in the past on these kind experiments testing for an important common shock in the economy usually revolved around the fact that many macro time series are highly correlated. Hence, one could argue that the common theme identified in these SVARs is a result of the high correlation rather than an independent underlying component. Table 4 shows the correlations between the variables used as measures of

[33]Using nominal treasury returns instead, the impulse responses of TFP and hours show a significant decline in response to a treasury news shock.

[34]The remaining FEVDs and IRs can be found in the Appendix.

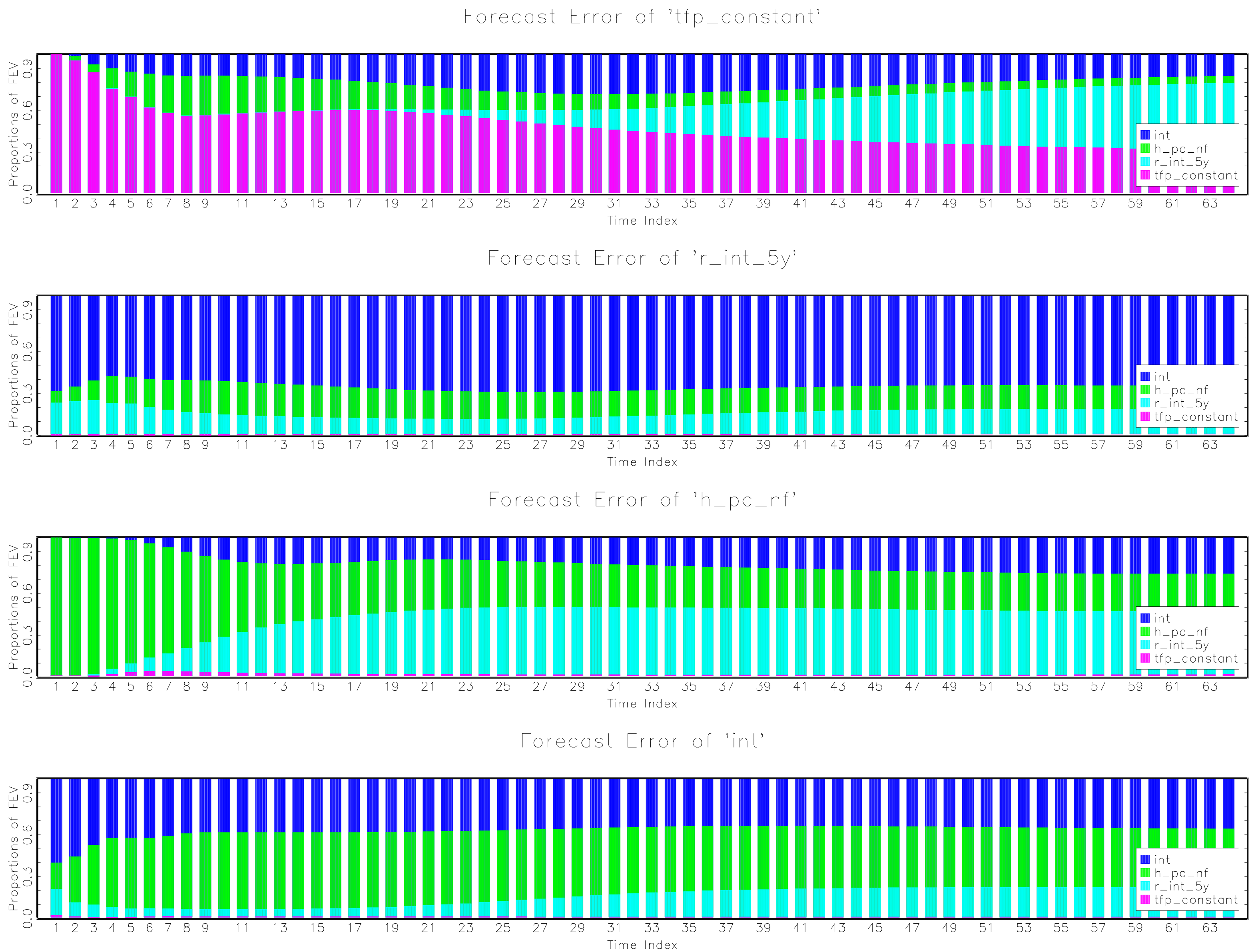

Figure 10: Long-run FEVDs of identification A with real return of 5 year treasuries, 1962Q1-2004Q1

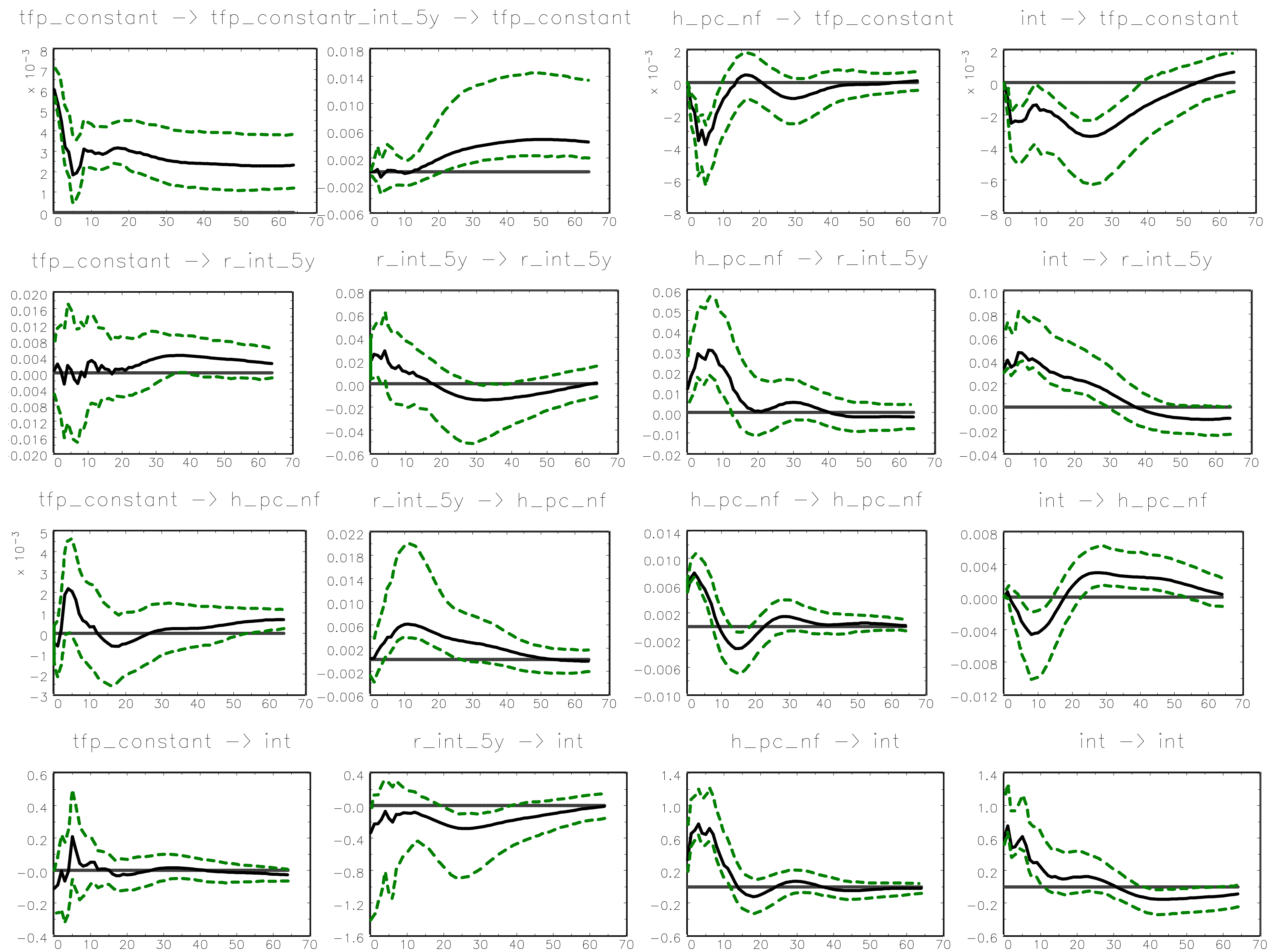

Figure 11: Long-run IRs of identification A with real return of 5 year treasuries, 1962Q1-2004Q1, dashed lines represent 95% bootstrapped Hall confidence intervals.

an underlying news shock. One can observe that all variables except real interest rates are highly correlated with stock prices. This exception provides a valuable insight. If there is an underlying component that drives the business cycle, then it will be captured in the common behavior of stock prices and real interest rates.

3.5 Commodity Prices

Bernanke, Boivin and Elisaz (2005) pointed out that the counter-intuitive result of a positive initial reaction of inflation to a positive monetary shock is a common feature of SVARs. Some argued that this result is due to the monetary policy in the pre-Volcker period, where the Fed supposedly did not fully offset inflationary supply shocks. This policy could lead to a concurrence of continued price inflation and increases in interest rates in the data and therefore could lead to the observed correlation, commonly known as the price puzzle. In contrast to this hypothesis, Sims (1992) finds this behavior as well in VARs using French, German, Japanese and British data. As a possible solution Sims (1992), Bernanke and Mihov (1998) as well as Christiano, Eichenbaum and Evans (1999) added another variable into the SVAR system to ease the positive price response to monetary shocks – an index of commodity prices.

While these commodities are used as production inputs, their prices are supposed to be sensitive to changes in inflation forecasts, since they are after all regular, storable assets. Therefore, their prices could be employed by a central bank as a proxy for additional information available. Since commodities are in general tradable goods, not all changes in their prices must be caused by changes in U.S. demand or supply, but instead may also be caused by supply shocks, changes in economic activity in other countries or terms-of-trade shocks. The exchange rate does not necessarily help to identify these exogenous shocks because commodities are generally priced in U.S. Dollar.

In consideration of these relations, it is hard to settle on a reasonable set of assumptions beyond A and C, solely based on economic theory. Instead, I will rely on a causality analysis to sort things out. The Tables 5 and 6 provide some insights in the Granger and Instantaneous causality probabilities. For this analysis I will consider any causality relation statistically significant, if the probability that there is no causal relation, is equal or below the level of $\alpha = 5\%$. The variables are organized in the following order: TFP, the inverse relative price of investment, S&P 500 index, hours, federal funds rate, the monthly average of Brent crude oil in dollar per barrel, the Commodity Research Bureau (CBR) commodity spot price index and the CBR commodity spot price index for raw materials.[35]

[35]Again, only transformed time series were used, the same remarks concerning employed methods

B / A	tfp_const	pi	sp_p	hours	int	oil	com	com_raw
tfp_const	-	0.0255	0.3320	0.1037	0.1151	0.2357	0.3294	0.1462
pi	0.1431	-	0.3516	0.9057	0.1436	0.3056	0.0144	0.0150
sp_p	0.0010	0.1027	-	0.0000	0.0005	0.7387	0.3091	0.0082
hours	0.0000	0.6330	0.3586	-	0.0000	0.2020	0.0819	0.0450
int	0.0000	0.5597	0.0094	0.0002	-	0.2129	0.3422	0.2939
oil	0.0970	0.0184	0.1940	0.0008	0.3618	-	0.1204	0.0657
com	0.0379	0.0002	0.0773	0.1698	0.0467	0.3288	-	0.0451
com_raw	0.0008	0.0017	0.0394	0.2919	0.0284	0.2420	0.1153	-

Table 5: Granger-Causalities, p-values, 6 lags, H_0: A does not Granger-cause B

The first result of the analysis is that there is no factor which has a significant instantaneous causal connection to oil prices. Furthermore, there is no factor that significantly Granger-causes oil prices within six quarters and there are only two factors, that is hours and the relative price of investment, that are significantly Granger-caused by oil prices. In general, these causality measures are only valid in the linear space. Moreover, it is common belief that oil prices are heavily important in economic activity. Therefore, one can conclude, that the relation is likely to be nonlinear. Since the methods I employ here are not able to cope with such a relation, I will exclude oil prices from the analysis and refer to Hamilton (2003), who investigates nonlinear oil price effects, instead.

as in the data section of the baseline model are valid. The Appendix provides a list of applied transformations and time series. The Granger causality probabilities reported are estimated without possible cointegration relations.

A \ B	tfp_const	pi	sp_p	hours	int	oil	com	com_raw
tfp_const	-	0.4915	0.0134	0.0791	0.0004	0.3401	0.1912	0.0320
pi	-	-	0.0961	0.0091	0.2721	0.5677	0.0001	0.0071
sp_p	-	-	-	0.0132	0.1023	0.1668	0.6336	0.8619
hours	-	-	-	-	0.0000	0.5952	0.0010	0.0000
int	-	-	-	-	-	0.4574	0.0000	0.0000
oil	-	-	-	-	-	-	0.3897	0.4336
com	-	-	-	-	-	-	-	0.0000
com_raw	-	-	-	-	-	-	-	-

Table 6: Contemporaneous Causalities, p-values, 6 lags, H_0: No instantaneous causality between A and B

The second result relies on the CBR commodity price index, because it is not Granger-caused by any variable except the relative price of investment and exhibits, in contrast to the spot price index, no significant instantaneous relation to neither TFP nor stock prices. This provides evidence to justify an assumption of no impact effect of commodity prices on stock prices.[36] Furthermore, if one assumes perfect competition in the long-run, firms should have to pass-trough all long-run changes in commodity prices, hence stock prices should not be affected by commodity price shocks in the long-run. Henceforth, I will join these two restrictions into assumption E. Although assumption A and C are not completely accepted by the causality measures, it seems reasonable to continue to use them, since they are based on common economic theory and provide comparability to earlier results. In summary, the following assumptions are used to identify the commodity shock in the baseline system:[37]

$$B := \begin{bmatrix} * & 0 & 0 & 0 & 0 \\ * & * & * & * & * \\ * & 0 & * & * & * \\ * & * & * & * & 0 \\ * & * & * & * & * \end{bmatrix} \qquad \Xi B := \begin{bmatrix} * & * & * & 0 & 0 \\ * & * & * & * & * \\ * & 0 & * & * & * \\ * & * & * & * & 0 \\ * & * & * & * & * \end{bmatrix}.$$

[36]The p-value for no instantaneous causality is 0.6336. The p-value for commodities not Granger-causing stock prices within the first six quarters is 0.0773, hence significant. The reverse assumption of no impact effect of stock prices on commodity prices would have been better with a p-value of 0.3091 for stock prices not Granger-causing commodity prices, but this assumption leads to a singular B matrix and the SVECM can not be estimated. Hence the former is used.

[37]The Johansen trace test does not reject the hypothesis of three cointegrating vectors (p-value 0.1547) and the AIC suggests again six lags (five lags in differences), hence I will continue to use these parameters.

The resulting dynamics presented in Figures 12 and 13 are as follows: Commodity shocks have a positive short-run effect on productivity and a negative effect on economic activity as well as an positive short-run effect on interest rates. An interesting result for me is that news shocks affect commodity prices on impact, though not significantly, which is consistent with portraying commodities as assets. But news shocks also lead to a temporary decline of commodity prices that coincides with the realization of the permanent increases in productivity. This description is compatible with an innovation, which takes time and resources, i.e. commodities and hours, to implement and then permanently decreases the resources needed for the same output by increasing productivity. The reason we do not see a permanent decline, but only a temporary dip in the impulse responses of hours and commodity prices, might lie in the permanent increase in output that follows when the production capacities increase. Another compelling feature is the response of productivity on a commodity shock: The significantly positive reaction might hint to a, at least at the margin, decreasing returns to scale production function, which is not surprising given that most costs are fixed in the short-run. In addition, the impulse responses of hours and commodity prices with respect to each other are compelling: While a positive preference shock increases on impact commodity prices, a commodity shock decreases hours. This is a positive indication of the estimated dynamics for the identification of the SVECM, since hours and commodities are by conventional wisdom complementary inputs in production. This means that an increase in commodity prices, decreases the demand for commodities and due to its complementary nature also the demand for hours, and vice versa. The complimentary nature of commodities explains the huge relative importance of preference shocks for commodity prices. It essentially means, that although commodities and economic activity, as measured in hours, are deeply interconnected, mostly economic activity affects commodity prices and not the other way around. Hence commodity shocks are mostly unimportant for economic activity and commodity prices just reflect economic activity and only to a small extent external and supply shocks, which mostly affect commodity prices on long-run horizons.

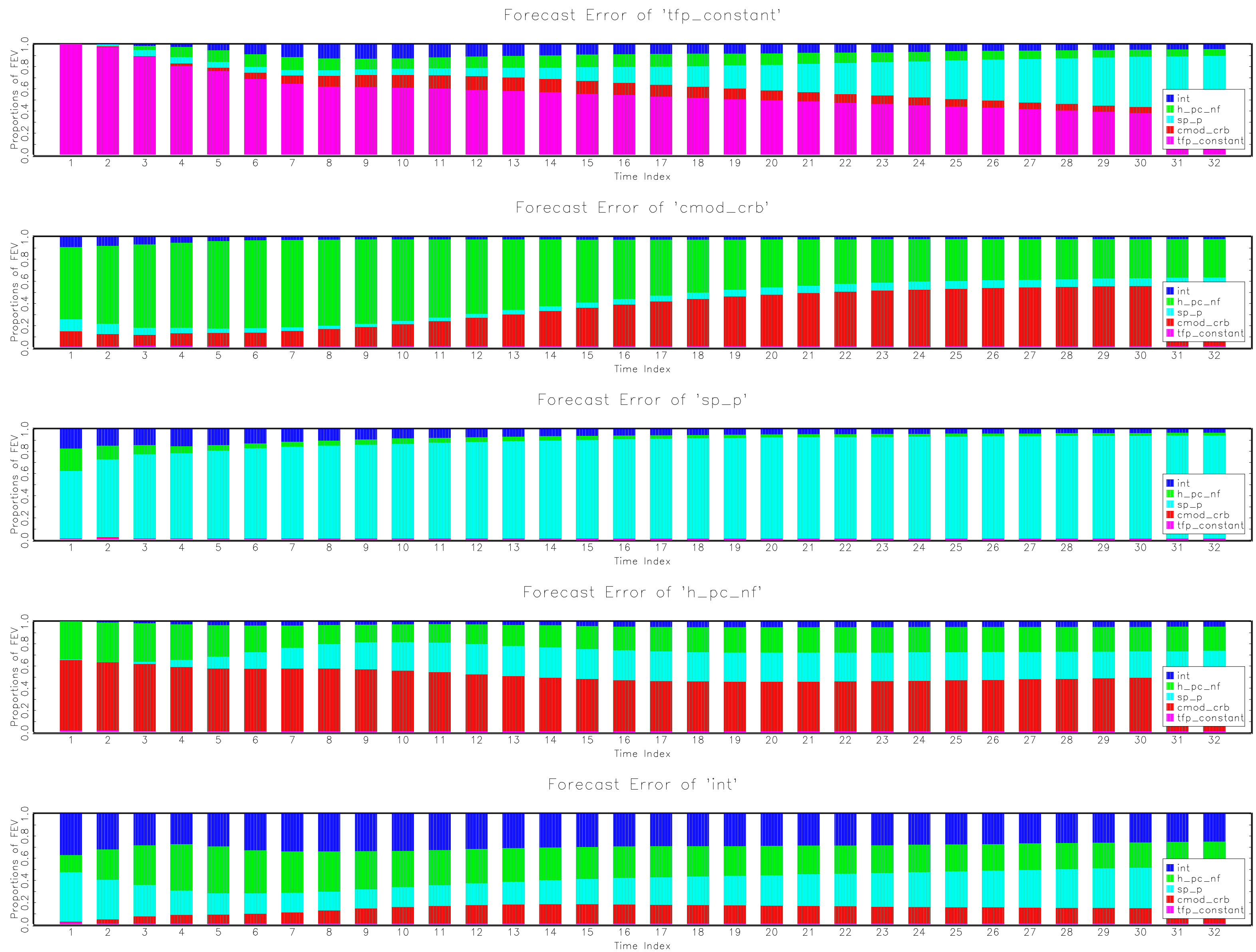

Figure 12: FEVDs of identification ACE with a commodity price index, 1955Q1-2008Q4

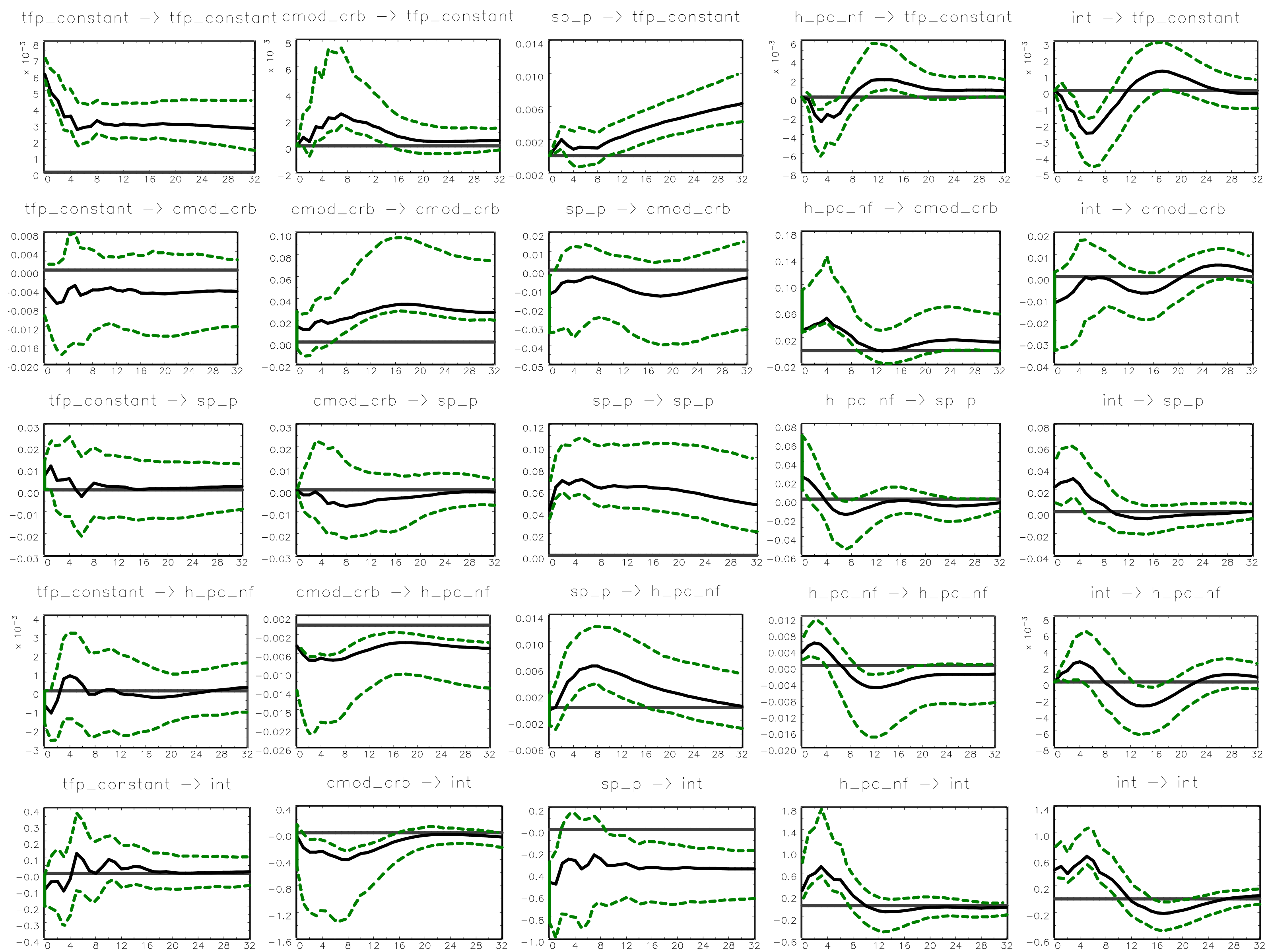

Figure 13: IRs of identification ACE with a commodity price index, 1955Q1-2008Q4, dashed lines represent 95% bootstrapped Hall confidence intervals.

4 Conclusion

This paper employed the VAR methodology to search for possibilities of a news shock identification. First of all, the results provide evidence for the hypothesis that news shocks represent anticipated movements in economic activity as the treasuries experiment show. Secondly, the economic interpretation of the treasuries identification, the IST identification as well as the patent shock identification are all consistent with the hypothesis of a technological nature of news shocks. The broad news shock experiment provides reasons that anticipated technological innovations are more likely to affect small companies first. While all identifications support a high importance of news shocks in fluctuations of economic activity, the estimates coincidently describe a news shock as a technological innovation that takes economic activity, that is hours and commodities, over a considerable time frame to implement, before productivity actually increases. All things considered, the presented results are consistent with the findings of Beaudry and Portier (2006).

The commodity analysis provided evidence for the possibility of nonlinear relations among key economic variables as oil and economic activity. Therefore, nonlinearities can not be ruled out, which limits the credibility of the results, but also provides reasons for further investigations concerning the nature of an anticipated technology shock. The broader news shock identification raises further questions with respect to asymmetric implementation of technological shocks: Why are small companies more heavily affected than large ones? While the answer might lie in the organizational structure or the asymmetric access to financial markets, splitting the broad stock market index into a variety of sectors might provide some insights. Furthermore, this analysis might provide some information on the distribution of technology shocks with respect to the impact of company size and sector.

The common stylized facts concerning the news shock are as follows: The news shock consistently causes a hump-shaped increase in economic activity with a peak within the first 15 quarters. Furthermore, the increase in economic activity consistently precedes gains in productivity, that are caused by the anticipated technology shock and materialize gradually, reaching their maximum impact approximately 15 quarters after the peak in economic activity. Neither surprise TFP shocks, commodity shocks nor monetary policy seem to be causal for the vast amount of economic fluctuations, although their connections to economic activity are strong in economic theory. Overall the consistency of the results is surprising. Given the variety and differences in nature how these measures are created and their importance for the economy it seems rather unlikely that they would be connected by an underlying common component. Nevertheless does the news shock theory joint with basic economic intuition proof very potent explaining these common themes in the SVAR measures.

References

[1] **Basu, S., J. G. Fernald, and M. S. Kimball**, "Are technology improvements contractionary?," *American Economic Review*, —2006—, *96* (5), 1418–1448.

[2] **Beaudry, P. and B. Lucke**, "Letting Different Views about Business Cycles Compete," *Nber Macroeconomics Annual 2010*, 2010, *2010*, 413–455.

[3] ——— **and F. Portier**, "Stock prices, news, and economic fluctuations," *American Economic Review*, —2006—, *96* (4), 1293–1307.

[4] **Bernanke, B. S. and I. Mihov**, "Measuring monetary policy," *Quarterly Journal of Economics*, —1998—, *113* (3), 869–902.

[5] ——— **and M. Gertler**, "Inside the Black-Box - the Credit Channel of Monetary-Policy Transmission," *Journal of Economic Perspectives*, —1995—, *9* (4), 27–48.

[6] ——— **, J. Boivin, and P. Eliasz**, "Measuring the effects of monetary policy: A factor-augmented vector autoregressive (FAVAR) approach," *Quarterly Journal of Economics*, —2005—, *120* (1), 387–422.

[7] **Beveridge, S. and C. R. Nelson**, "A New Approach to Decomposition of Economic Time-Series into Permanent and Transitory Components with Particular Attention to Measurement of the Business-Cycle," *Journal of Monetary Economics*, —1981—, *7* (2), 151–174.

[8] **Bry, G. and C Boschan**, "Cyclical Analysis of Time Series: Selected Procedures and Computer Programs," *NBER*, —1971—, *1971* (20).

[9] **Chari, V. V., P. J. Kehoe, and E. R. McGrattan**, "Are structural VARs with long-run restrictions useful in developing business cycle theory?," *Journal of Monetary Economics*, —2008—, *55* (8), 1337–1352.

[10] **Christiano, L. J., M. Eichenbaum, and C. Evans**, "The effects of monetary policy shocks: Evidence from the flow of funds," *Review of Economics and Statistics*, —1996—, *78* (1), 16–34.

[11] ——— **,** ——— **, and C. L. Evans**, "Monetary Policy Shocks: What have we learned and to what end?," in John B. Taylor and M. Woodford, eds., *Handbook of Macroeconomics*, Vol. 1, Amsterdam: Elsevier, —1999—.

[12] **Clarida, R., J. Gali, and M. Gertler**, "The science of monetary policy: A new keynesian perspective," *Journal of Economic Literature*, —1999—, *37* (4), 1661–1707.

[13] **Fama, E. F.**, "The Behavior of Stock-Market Prices," *Journal of Business*, —1965—, *38* (1), 34–105.

[14] ___ , "Stock Returns, Expected Returns, and Real Activity," *Journal of Finance*, —1990—, *45* (4), 1089–1108.

[15] **Fisher, D. C.**, "Technology Shocks Matter," *Federal Reserve Bank of Chicago*, October, 2003 —2003—, p. 43.

[16] **Fisher, J. D. M.**, "The dynamic effects of neutral and investment-specific technology shocks," *Journal of Political Economy*, —2006—, *114* (3), 413–451.

[17] **Granger, C. W. J.**, "Some Properties of Time-Series Data and Their Use in Econometric-Model Specification," *Journal of Econometrics*, —1981—, *16* (1), 121–130.

[18] **Greenwood, J., Z. Hercowitz, and P. Krusell**, "Long-run implications of investment-specific technological change," *American Economic Review*, —1997—, *87* (3), 342–362.

[19] **Hamilton, J. D.**, "What is an oil shock?," *Journal of Econometrics*, —2003—, *113* (2), 363–398.

[20] **Hansen, Peter Reinhard**, "Granger's representation theorem: A closed-form expression for I(1) processes," *The Econometrics Journal*, March 2005, *8* (1), 23–38.

[21] **Johansen, S.**, "Estimation and Hypothesis-Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models," *Econometrica*, —1991—, *59* (6), 1551–1580.

[22] **Keynes, John Maynard**, *The general theory of employment, interest and money*, London,: Macmillan, —1936—.

[23] **Kydland, F. E. and E. C. Prescott**, "Time to Build and Aggregate Fluctuations," *Econometrica*, —1982—, *50* (6), 1345–1370.

[24] **Lütkepohl, Helmut**, *New introduction to multiple time series analysis*, Berlin ;: New York : Springer, —2005—.

[25] ___ **and Markus Krätzig**, *Applied time series econometrics* Themes in modern econometrics, Cambridge, UK ; New York: Cambridge University Press, —2004—.

[26] **Manski, Charles F.**, *Identification for prediction and decision*, Cambridge, Mass.: Harvard University Press, —2007—.

[27] **McCallum, B. T.**, "An optimization-based econometric framework for the evaluation of monetary policy - Comment," *Nber Macroeconomics Annual 1997*, —1997—, *12*, 355–359.

[28] **of Labor Statistics, United States Bureau**, *BLS handbook of methods*, U.S. Bureau of Labor Statistics, —1997—.

[29] **Pigou, A. C.**, *Industrial fluctuations*, London,: Macmillan and co., limited, —1927—.

[30] **Schmitt-Grohe, Stephanie and Martin Uribe**, "What's news in business cycles," *NBER*, August 2008 —2008—, *2008* (14215), 51.

[31] **Shiller, Robert J.**, *Irrational exuberance*, 2nd ed., Princeton, N.J.: Princeton University Press, —2005—.

[32] **Sims, C. A.**, "Macroeconomics and Reality," *Econometrica*, —1980—, *48* (1), 1–48.

[33] ___ , "Interpreting the Macroeconomic Time-Series Facts - the Effects of Monetary-Policy," *European Economic Review*, —1992—, *36* (5), 975–1000.

5 Appendix

5.1 Identification Scheme AB_1C

As pointed out earlier, the long-run neutrality of money is a common belief in economic theory. This can be incorporated in the SVECM to provide an additional credible restriction derived from economic theory. To compare the results to the baseline model above I will add this assumption to the identification scheme AB_1. Since the system was just identified and I want to avoid overidentification I will drop the assumption of no immediate effect of monetary policy shocks on the inverse relative price of investment. The identification scheme now looks as follows:

$$B := \begin{bmatrix} * & 0 & 0 & 0 & 0 \\ * & * & 0 & 0 & * \\ * & * & * & * & 0 \\ * & * & * & * & * \end{bmatrix} \qquad \Xi B := \begin{bmatrix} * & * & * & 0 & 0 \\ * & * & * & * & * \\ * & * & * & * & 0 \\ * & * & * & * & * \end{bmatrix},$$

where stars denote unrestricted entries. As the following figures show the results do not change much. The most notable change is the impulse response of the relative price of investment on the news shock which now leads to a permanent increase in the price of investment while the contributions of IST shocks to the variances stay small. Therefore, I conclude that the assumption C is valuable in the sense that it allows to abstain myself from one additional assumption on the newly added shock. Hence using this relatively credible assumption reduces the likelihood of a false set of identifying assumptions which would lead to a biased estimate by artificially decreasing the space of available estimators.

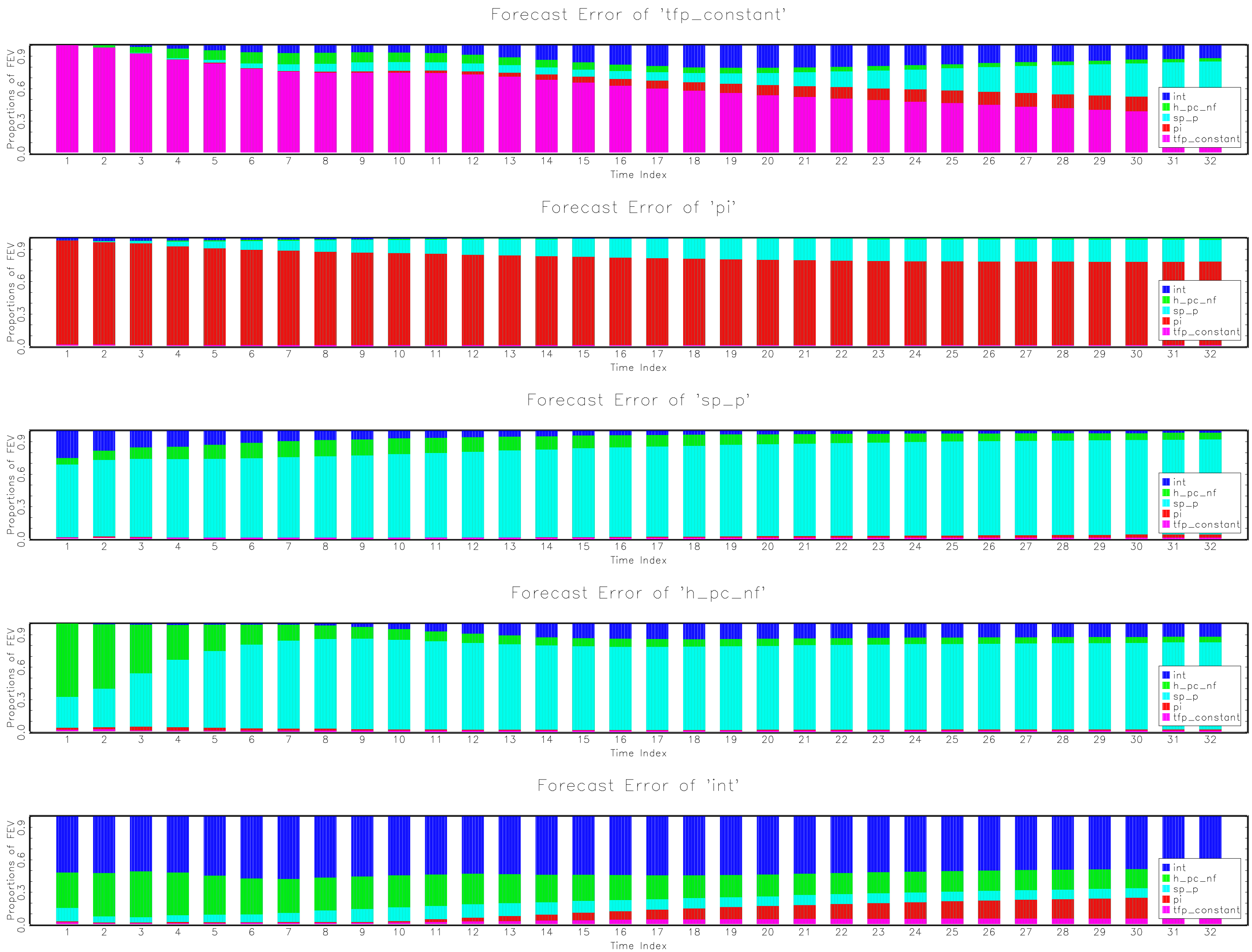

Figure 14: FEVDs of identification $\mathrm{A}B_1\mathrm{C}$ with TFP constructed using a constant labor share, 1955Q1-2008Q4

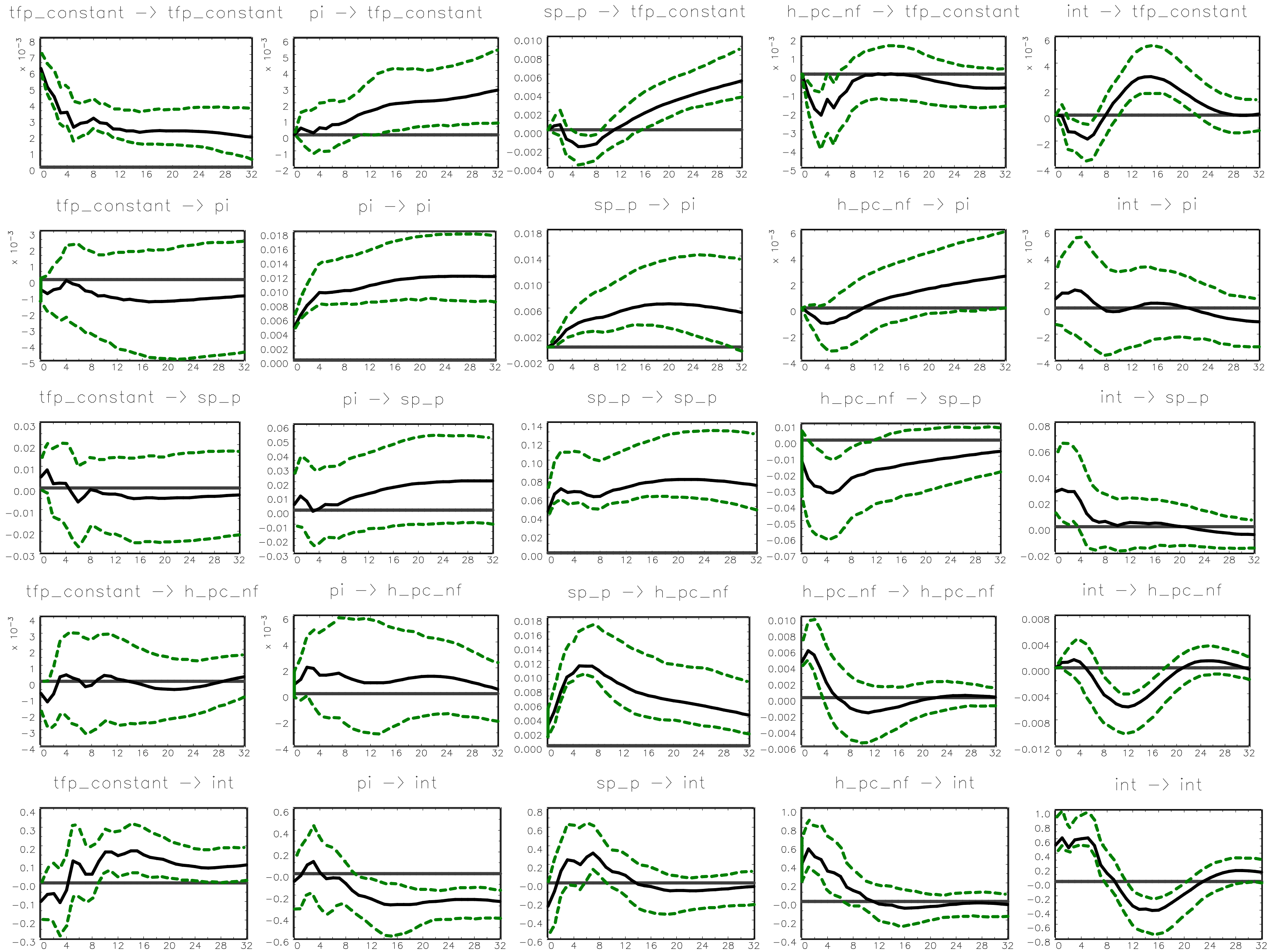

Figure 15: IRs of identification AB_1C with TFP constructed using a constant labor share, 1955Q1-2008Q4, dashed lines represent 95% bootstrapped Hall confidence intervals.

5.2 Long-run baseline system

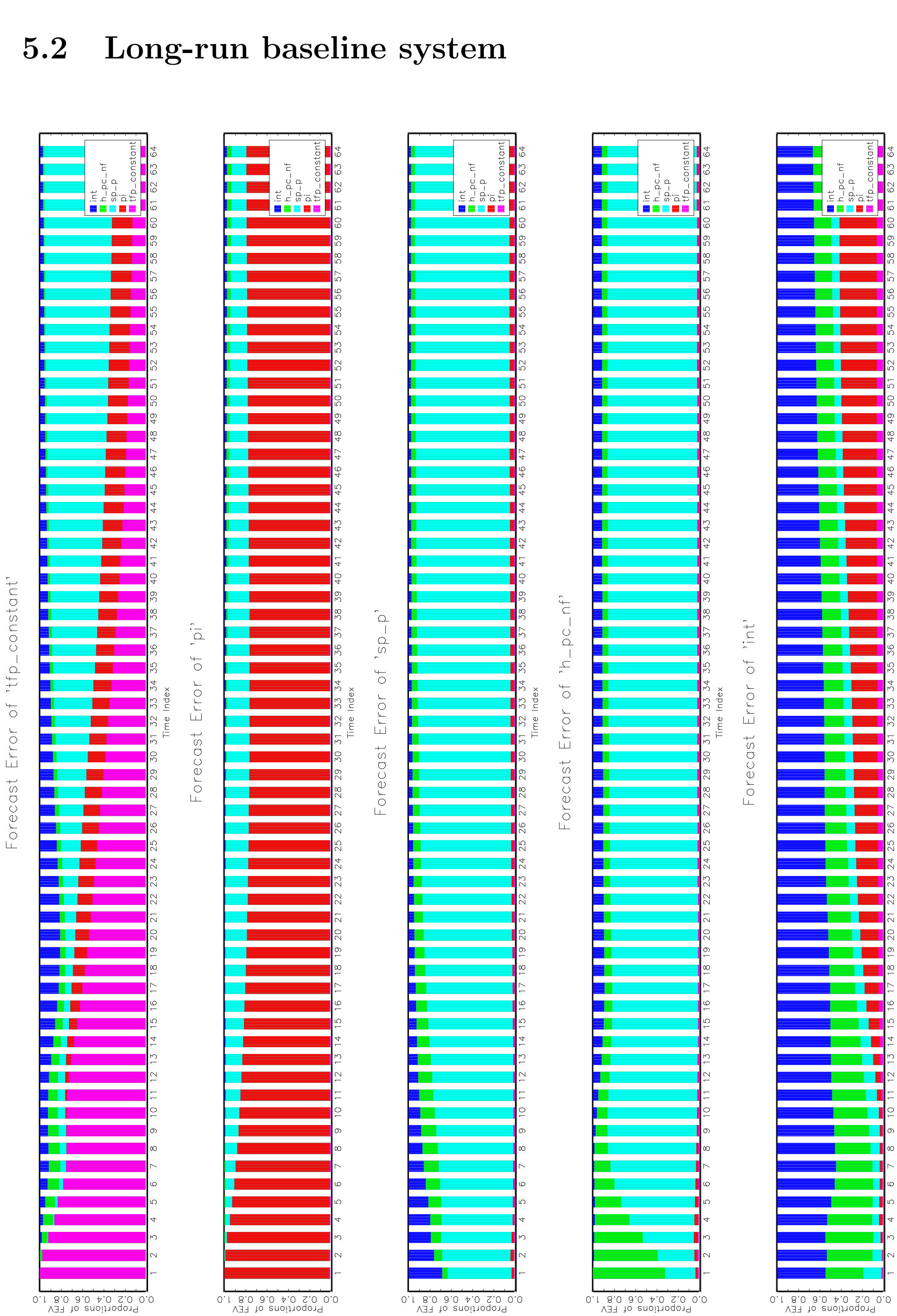

Figure 16: Long-run FEVDs of identification AB_1 with TFP constructed using a constant labor share, 1955Q1-2008Q4

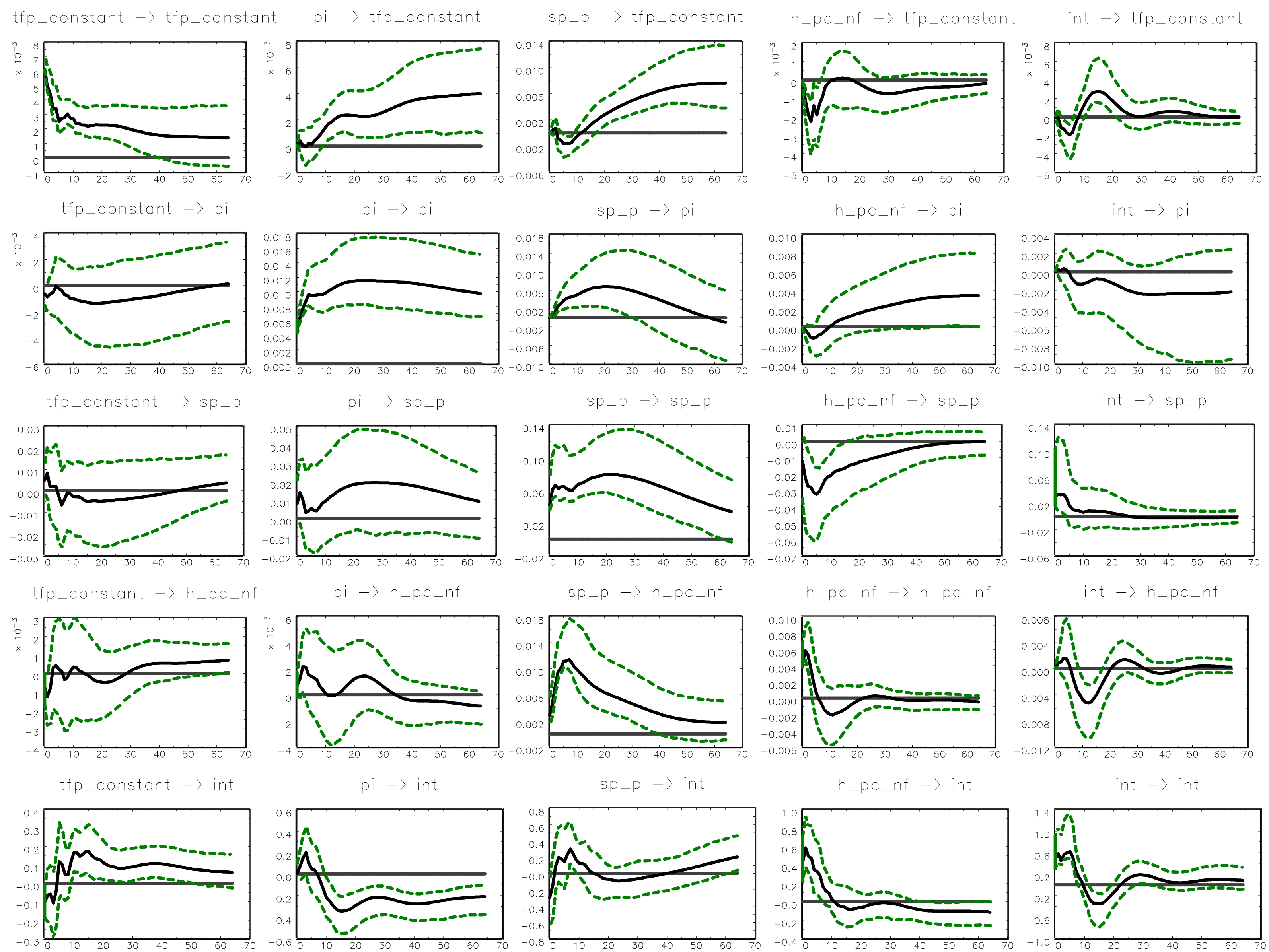

Figure 17: Long-run IRs of identification AB_1 with TFP constructed using a constant labor share, 1955Q1-2008Q4, dashed lines represent 95% bootstrapped Hall confidence intervals.

5.3 Tornqvist Index Specification in identification scheme $\mathbf{A}B_1$

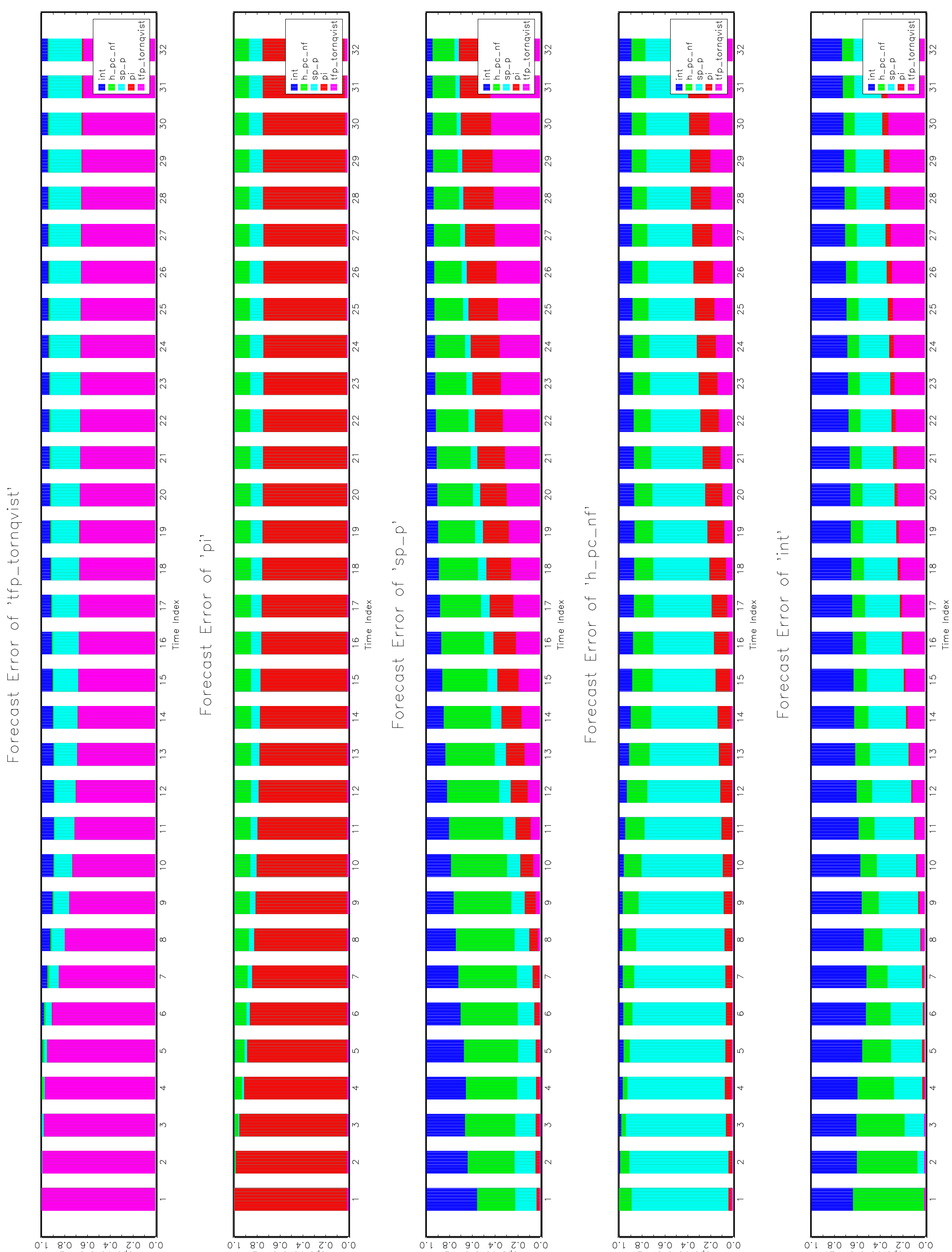

Figure 18: FEVDs of identification $\mathrm{A}B_1$ with TFP constructed using a Tornqvist specification, 1955Q1-2008Q4

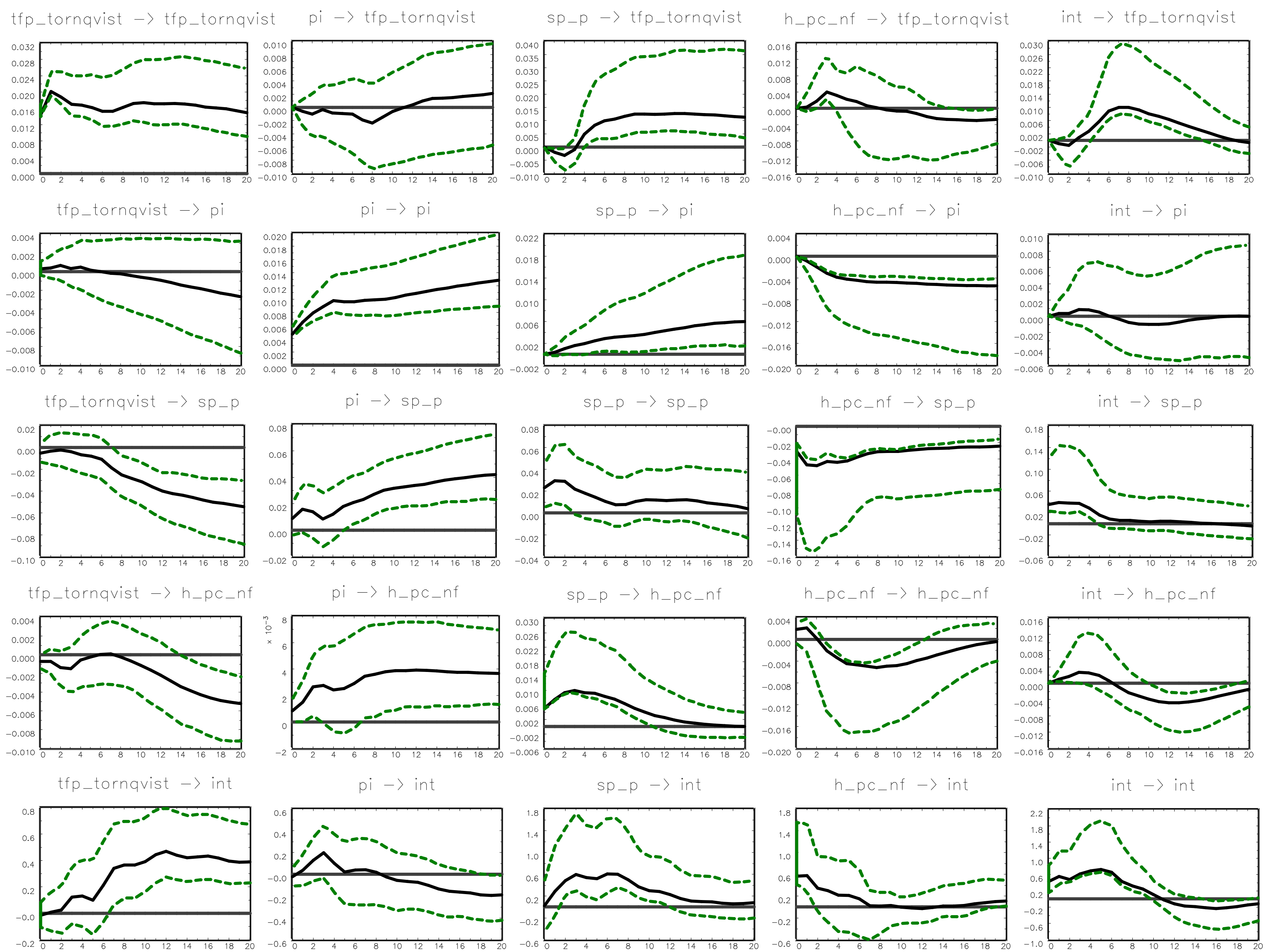

Figure 19: IRs of identification AB_1 with TFP constructed using a Tornqvist specification, 1955Q1-2008Q4, dashed lines represent 95% bootstrapped Hall confidence intervals.

5.4 Identification scheme $\mathbf{A}B_2$

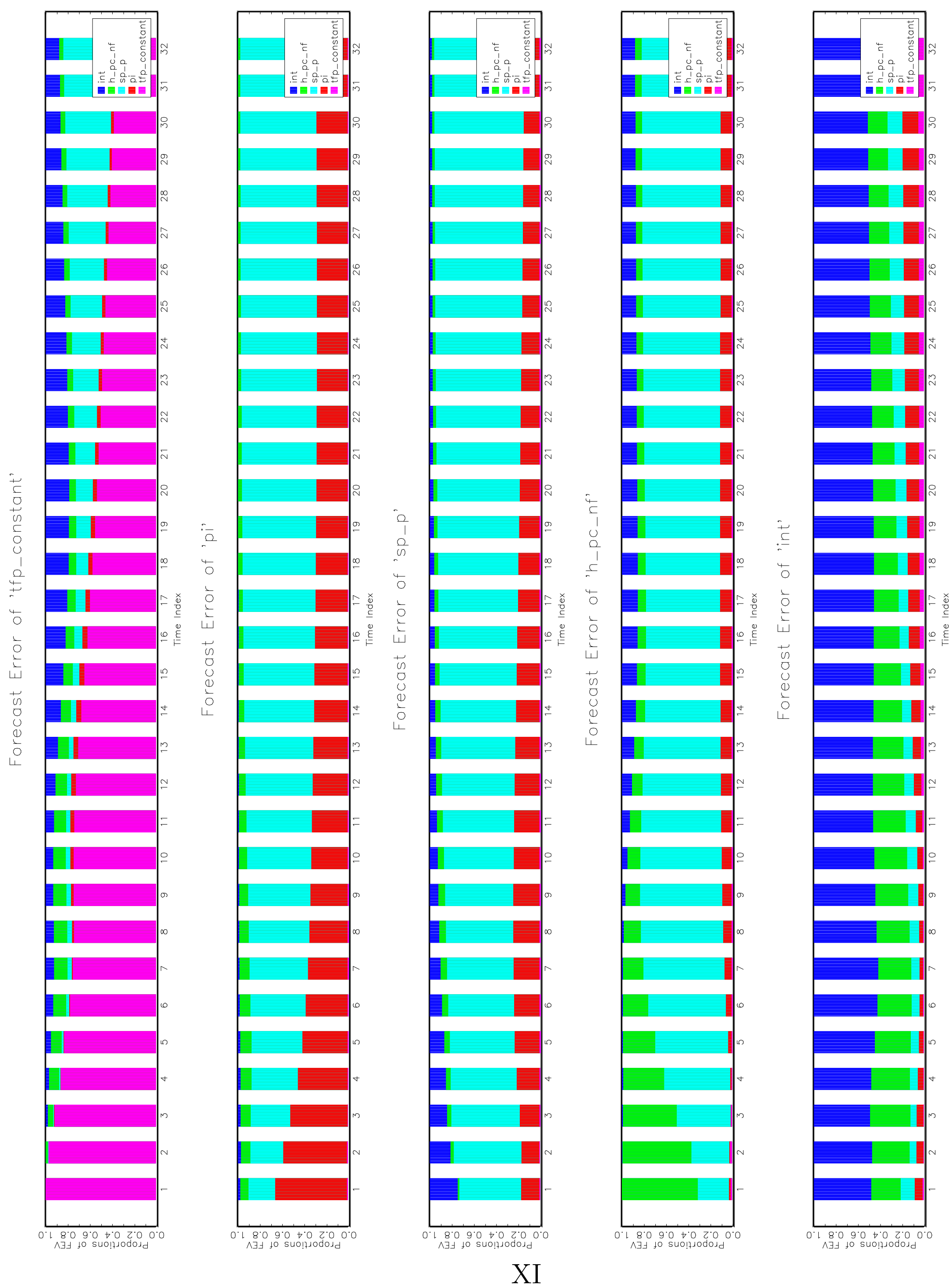

Figure 20: FEVDs of identification $\mathbf{A}B_2$ with TFP constructed using a constant labor share, 1955Q1-2008Q4

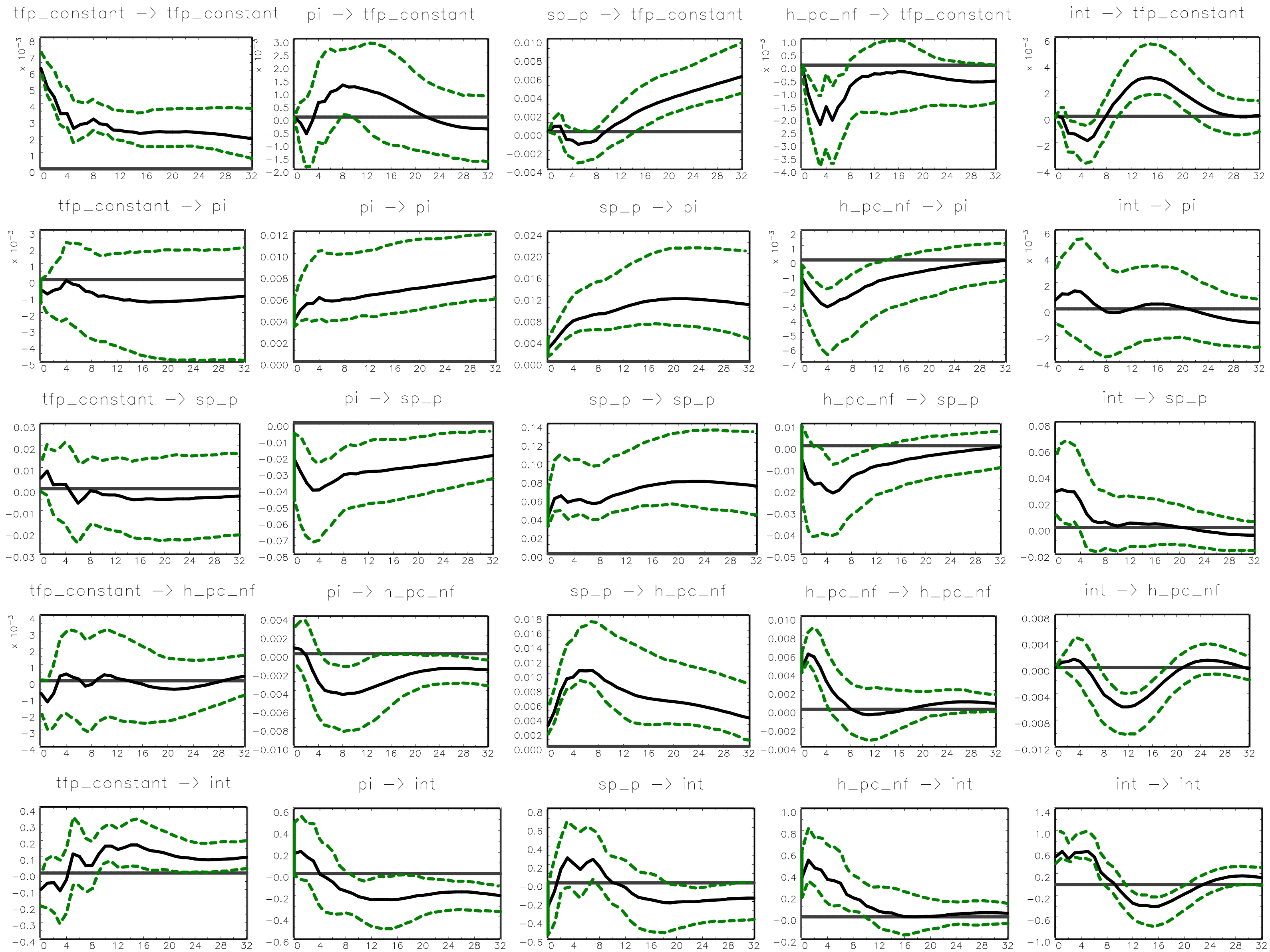

Figure 21: IRs of identification AB_2 with TFP constructed using a constant labor share, 1955Q1-2008Q4, dashed lines represent 95% bootstrapped Hall confidence intervals.

5.5 Identification scheme A and real treasury yields for various maturities

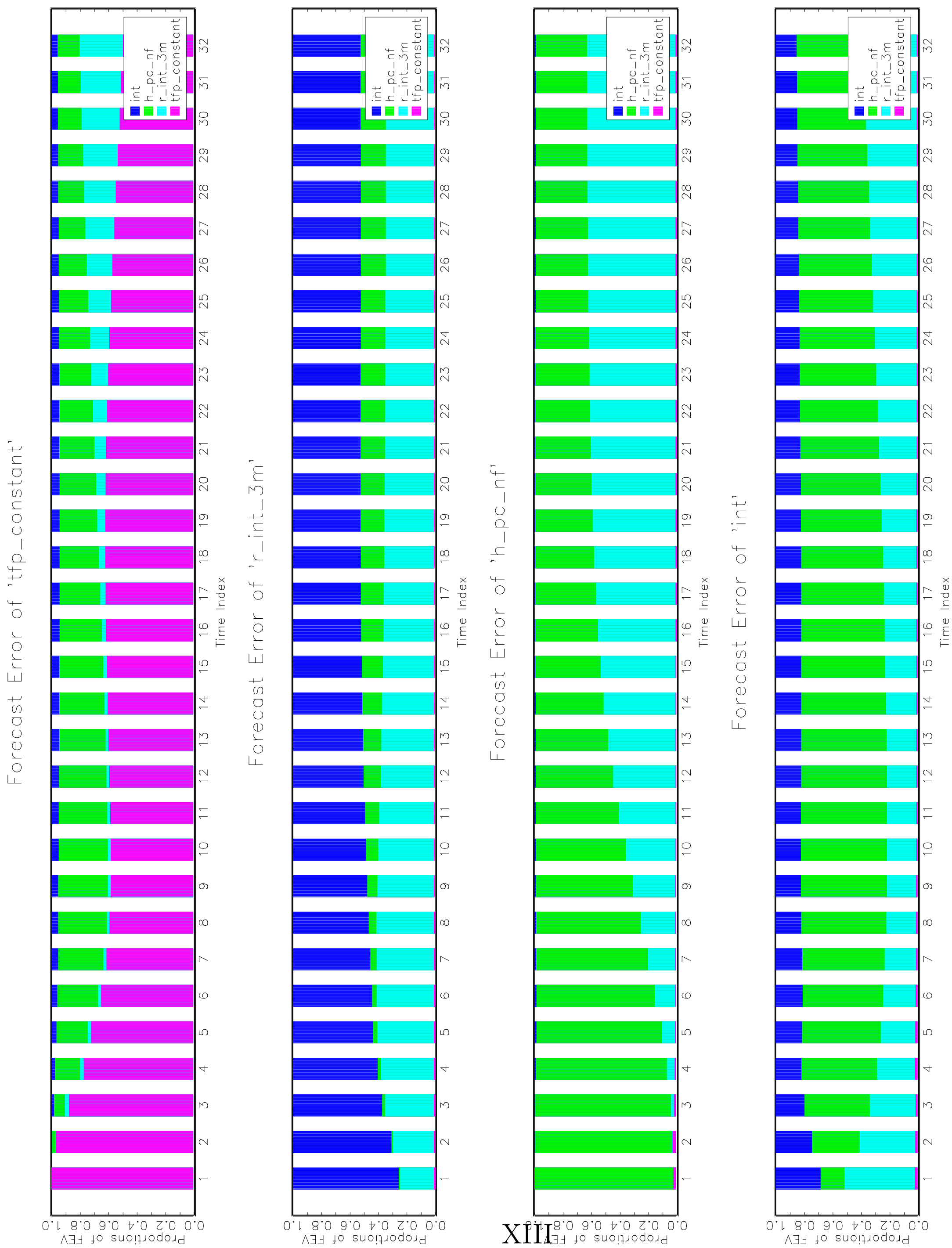

Figure 22: FEVDs of identification A with real return of 3 month treasuries, 1955Q1-2008Q4

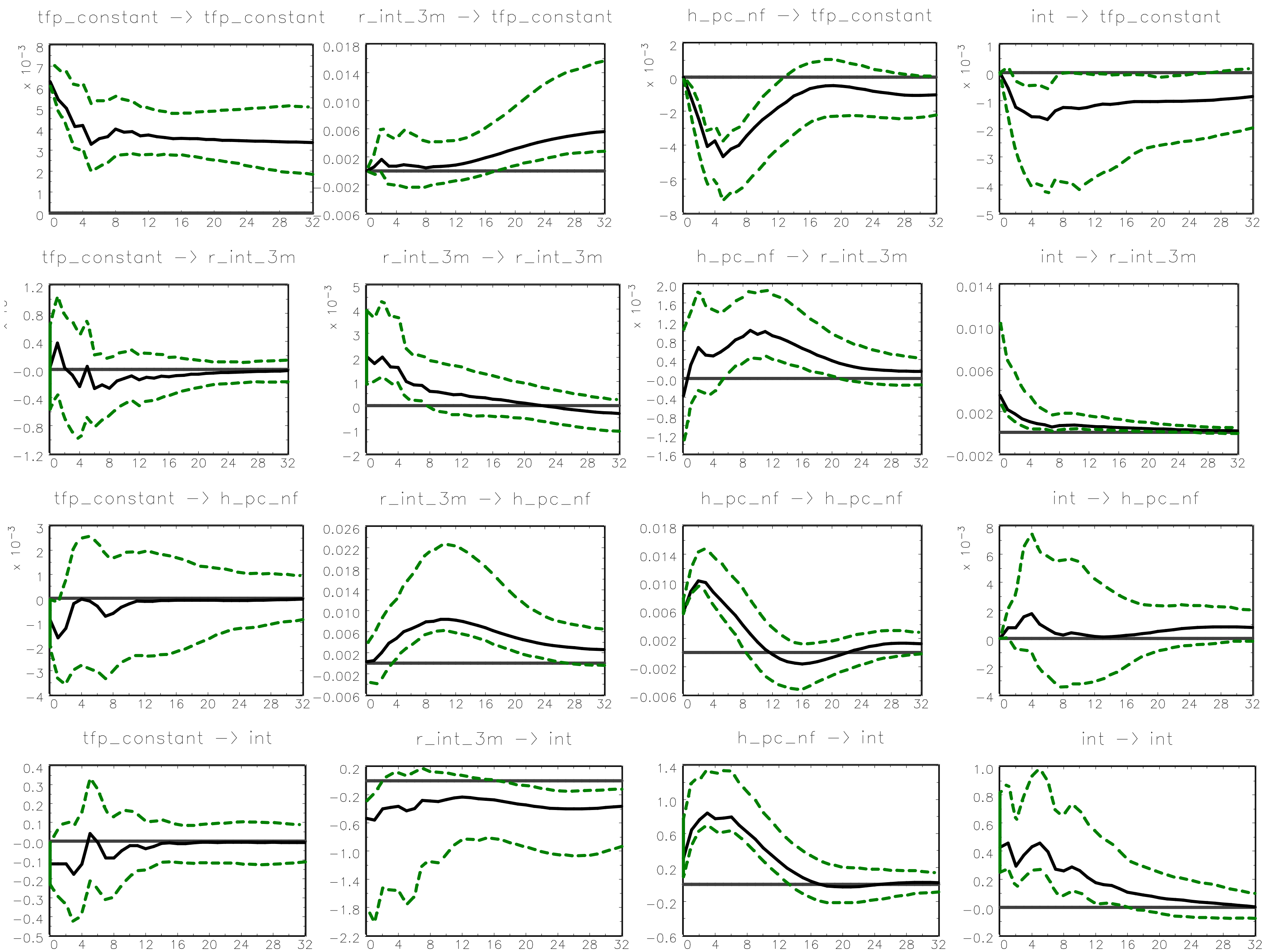

Figure 23: IRs of identification A with real return of 3 month treasuries, 1955Q1-2008Q4, dashed lines represent 95% bootstrapped Hall confidence intervals.

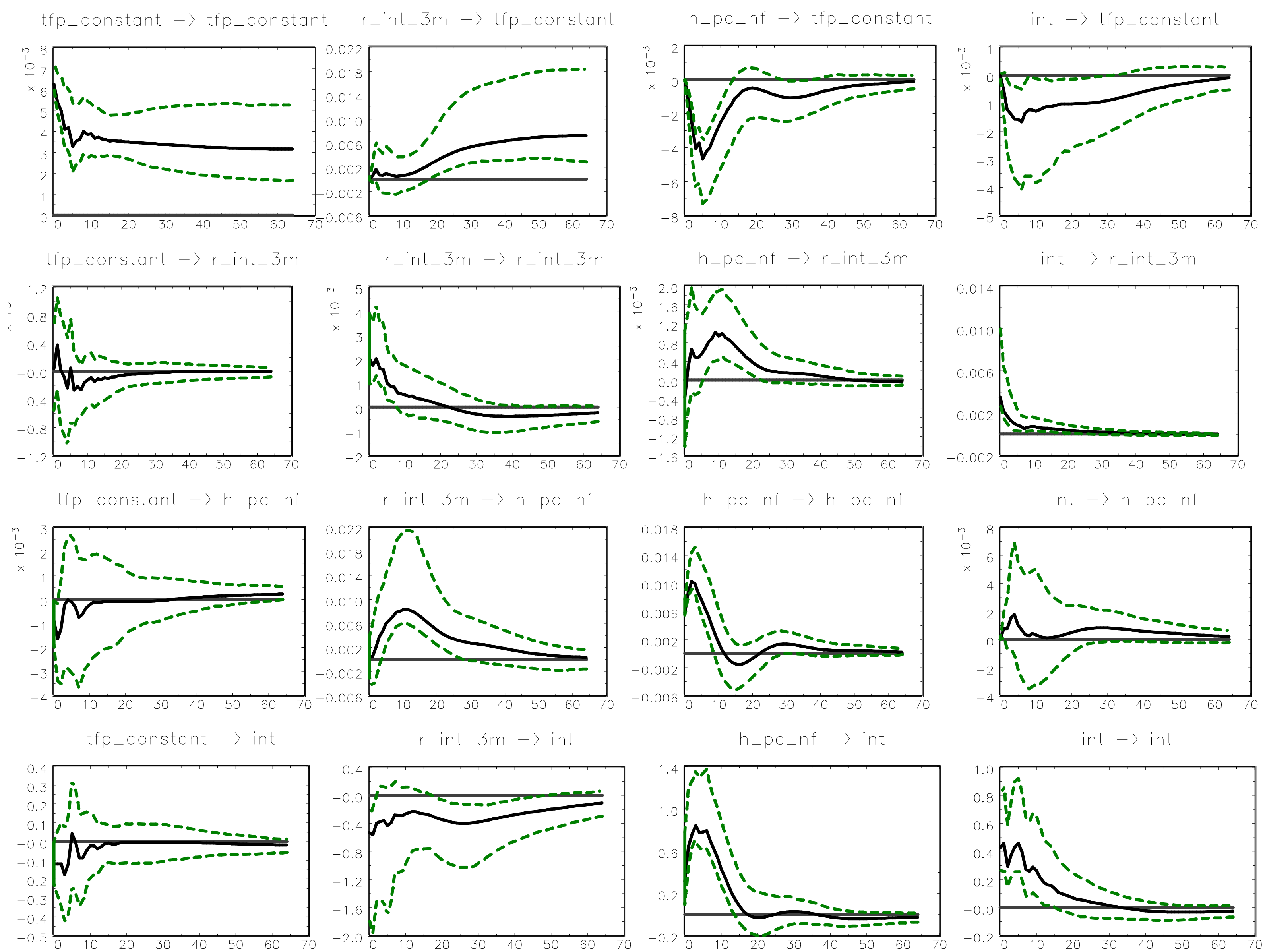

Figure 25: Long-run IRs of identification A with real return of 3 month treasuries, 1955Q1-2008Q4, dashed lines represent 95% bootstrapped Hall confidence intervals.

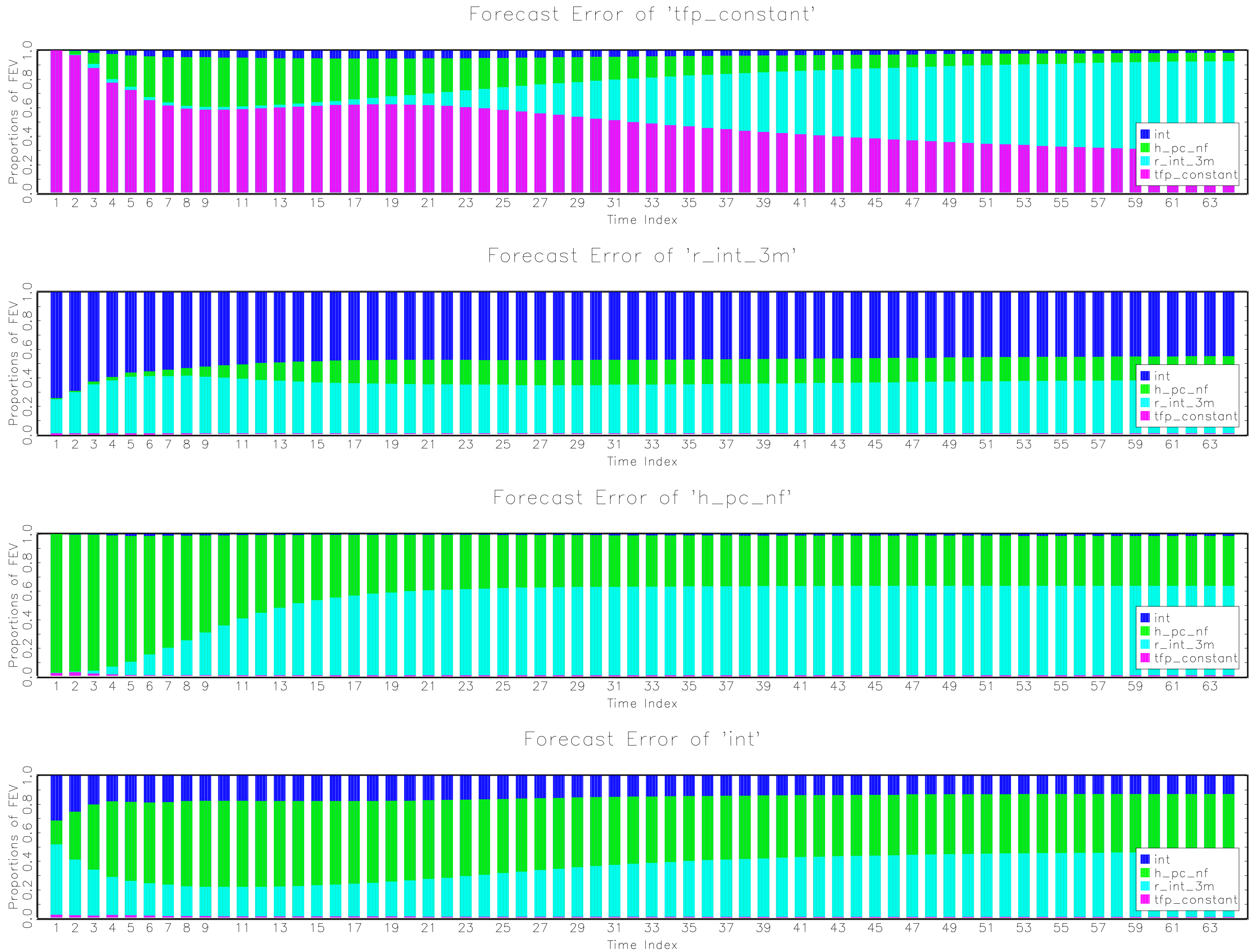

Figure 24: Long-run FEVDs of identification A with real return of 3 month treasuries, 1955Q1-2008Q4

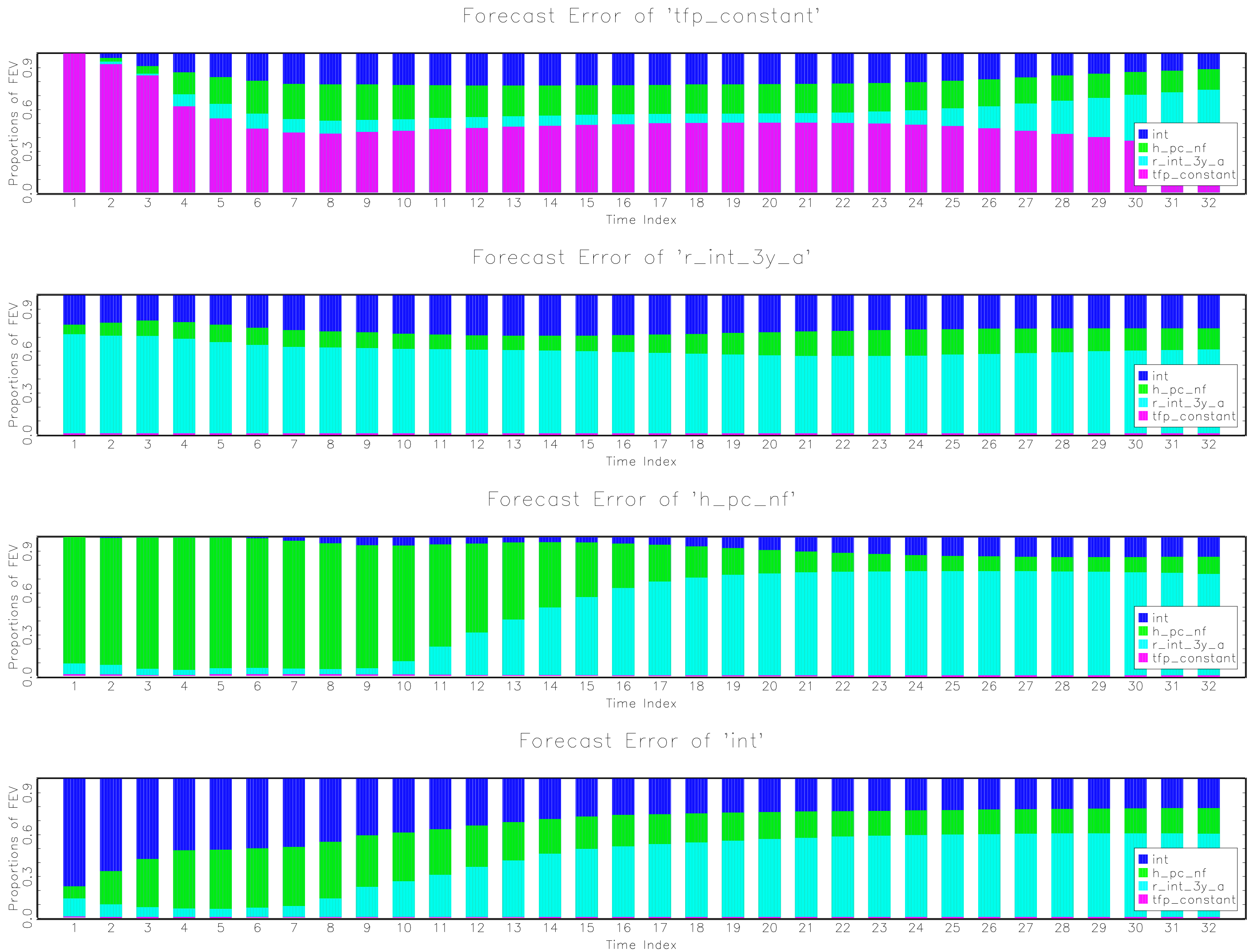

Figure 26: FEVDs of identification A with real return of 3 year treasuries, 1957Q1-2006Q1

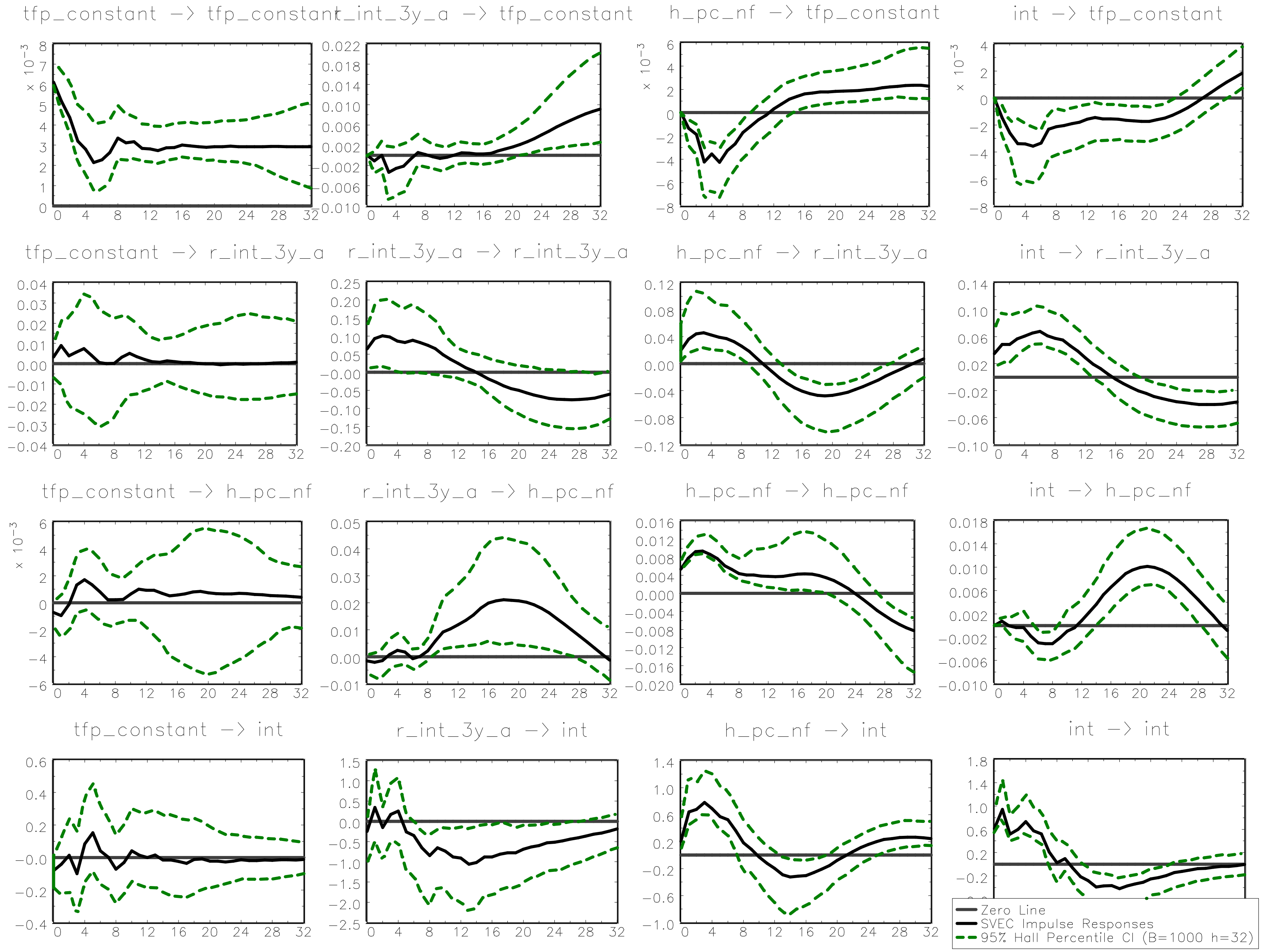

Figure 27: IRs of identification A with real return of 3 year treasuries, 1957Q1-2006Q1, dashed lines represent 95% bootstrapped Hall confidence intervals.

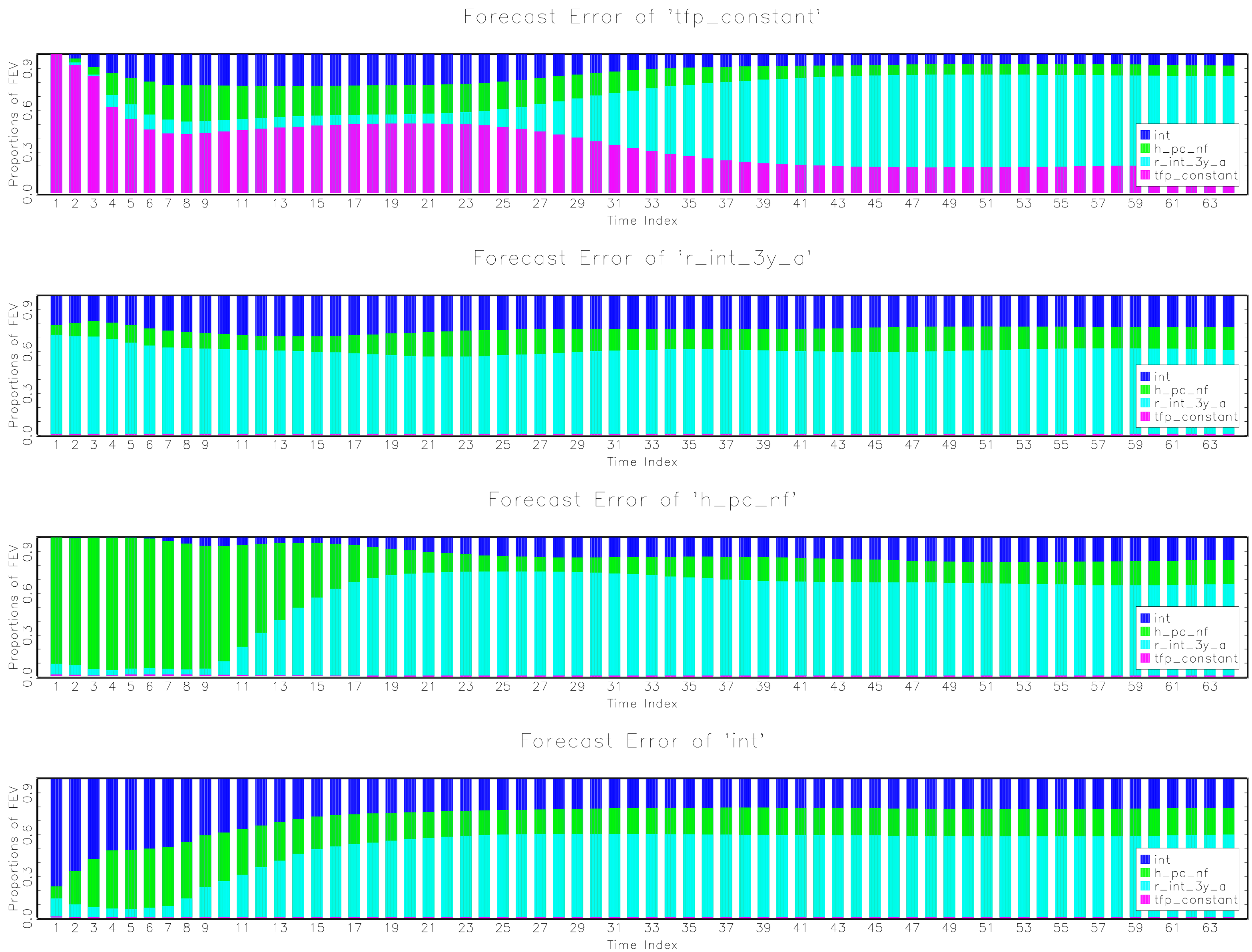

Figure 28: Long-run FEVDs of identification A with real return of 3 year treasuries, 1957Q1-2006Q1

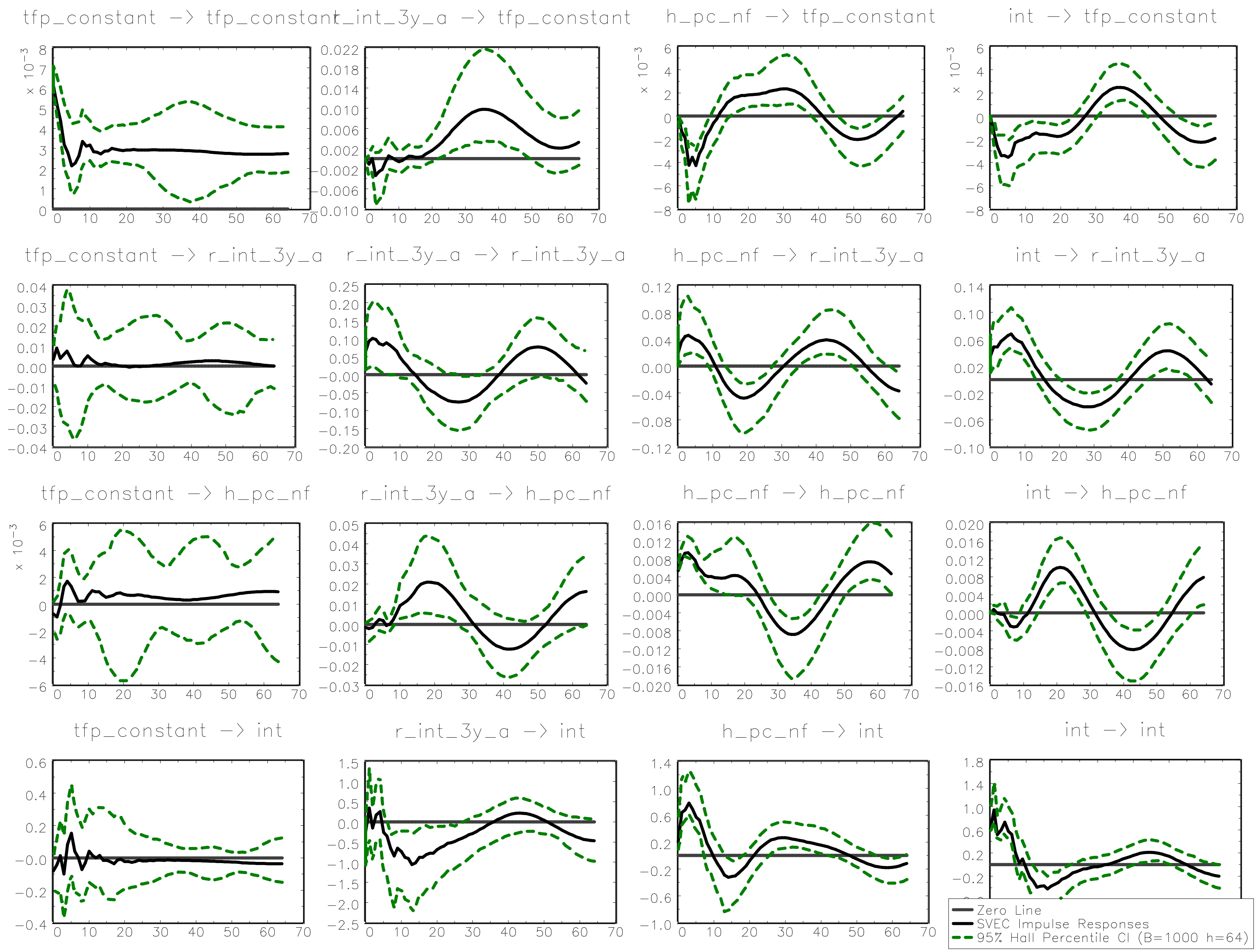

Figure 29: Long-run IRs of identification A with real return of 3 year treasuries, 1957Q1-2006Q1, dashed lines represent 95% bootstrapped Hall confidence intervals.

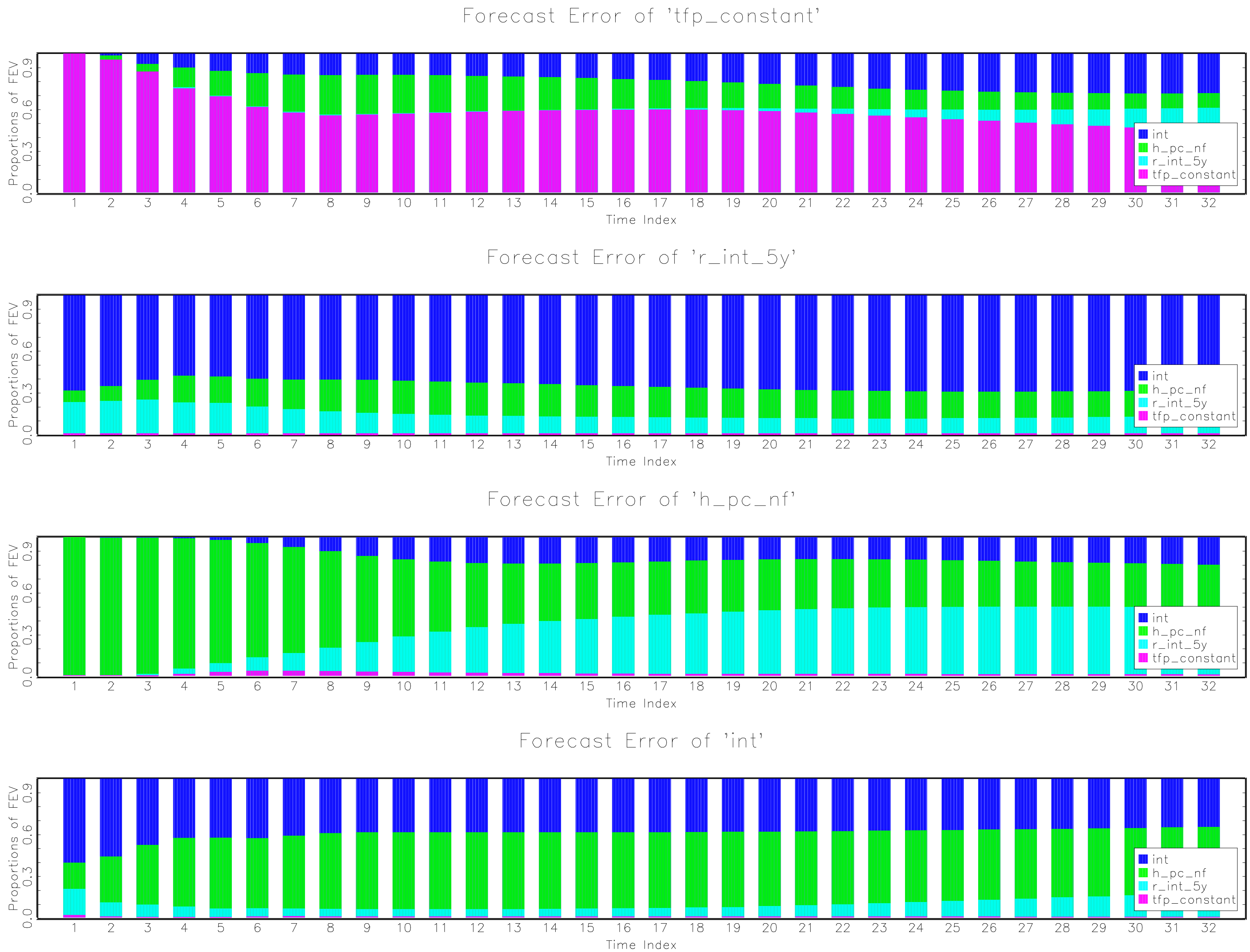

Figure 30: FEVDs of identification A with real return of 5 year treasuries, 1962Q1-2004Q1

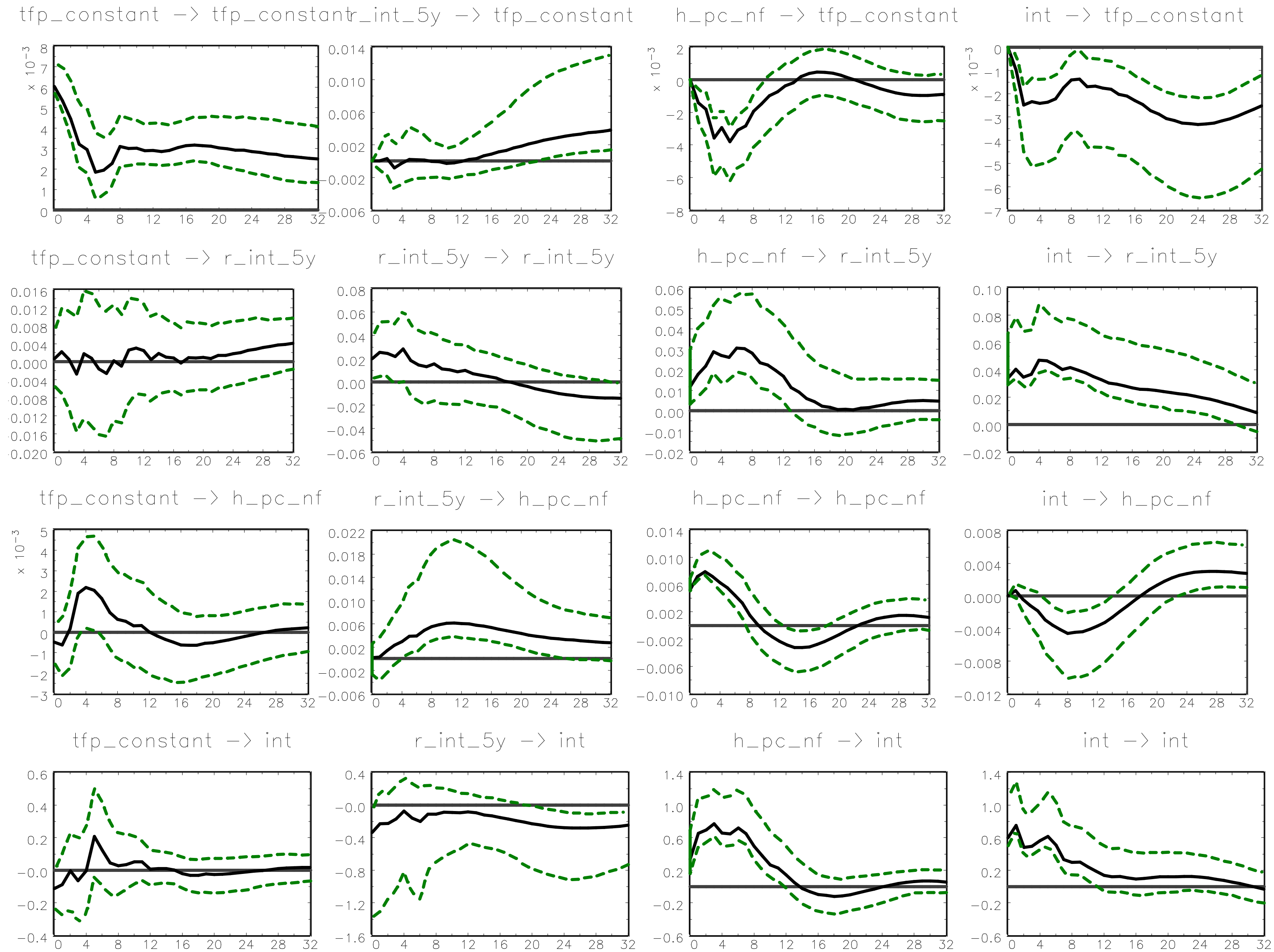

Figure 31: IRs of identification A with real return of 5 year treasuries, 1962Q1-2004Q1, dashed lines represent 95% bootstrapped Hall confidence intervals.

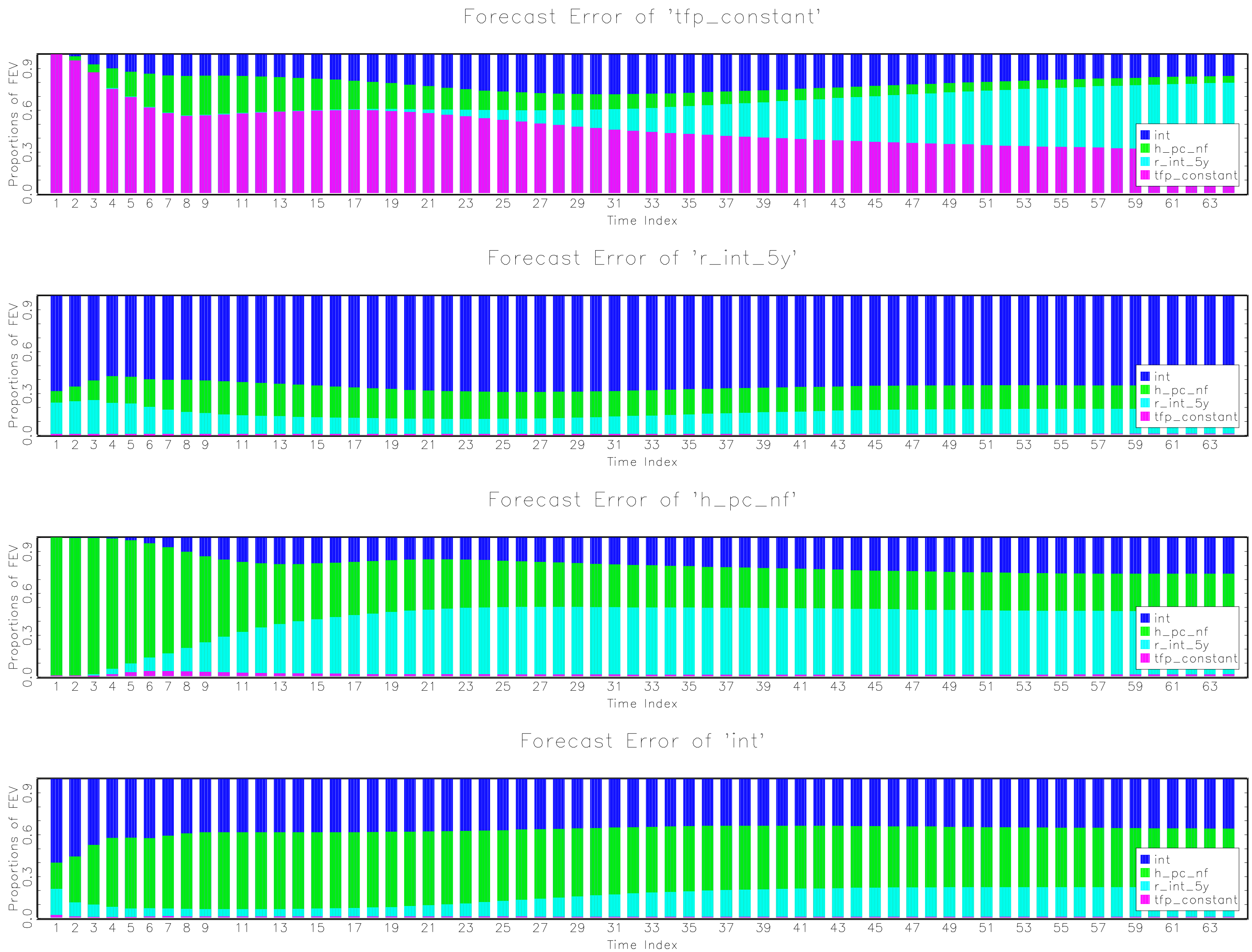

Figure 32: Long-run FEVDs of identification A with real return of 5 year treasuries, 1962Q1-2004Q1

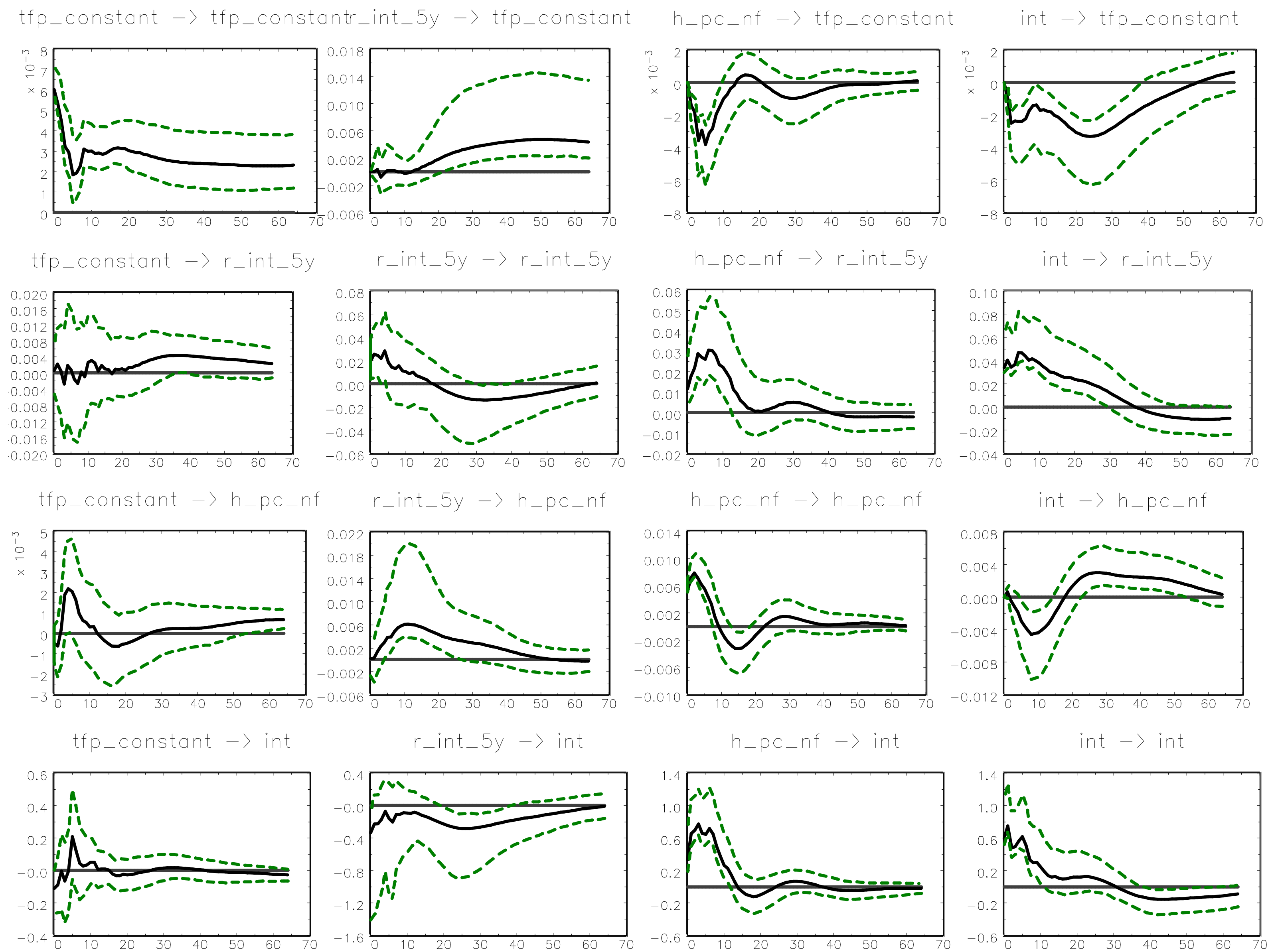

Figure 33: Long-run IRs of identification A with real return of 5 year treasuries, 1962Q1-2004Q1, dashed lines represent 95% bootstrapped Hall confidence intervals.

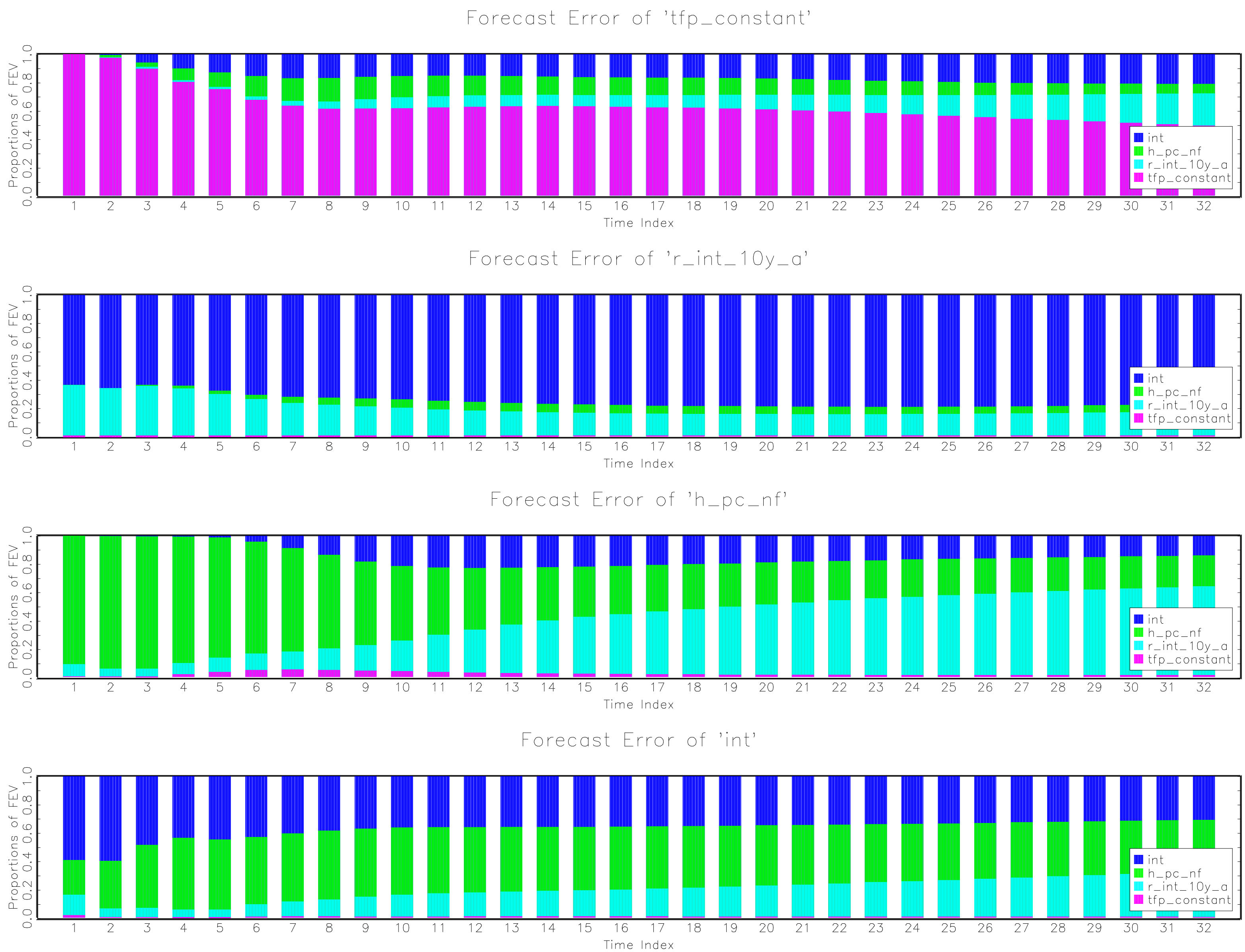

Figure 34: FEVDs of identification A with real return of 10 year treasuries, 1957Q1-1999Q1

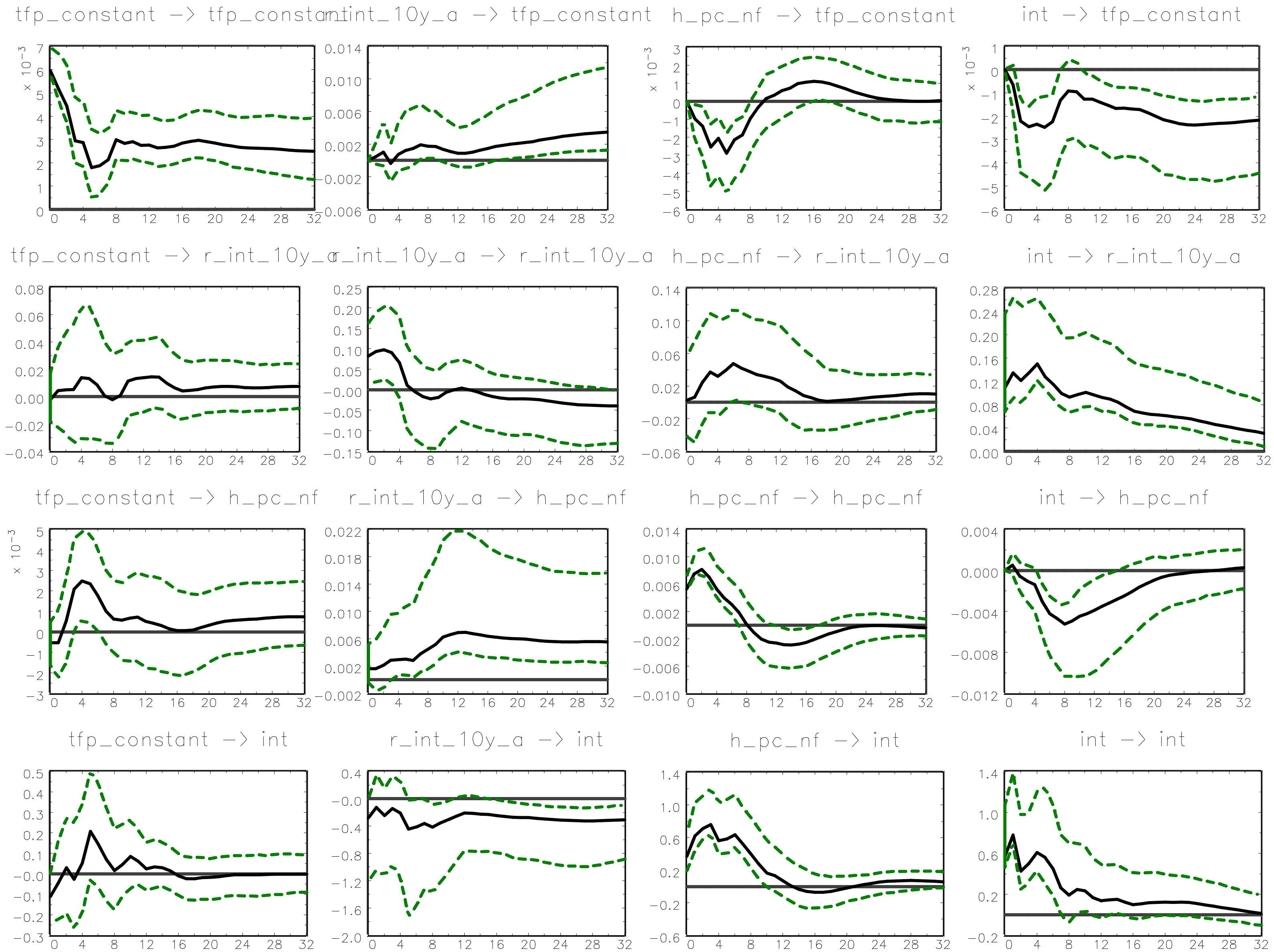

Figure 35: IRs of identification A with real return of 10 year treasuries, 1957Q1-1999Q1, dashed lines represent 95% bootstrapped Hall confidence intervals.

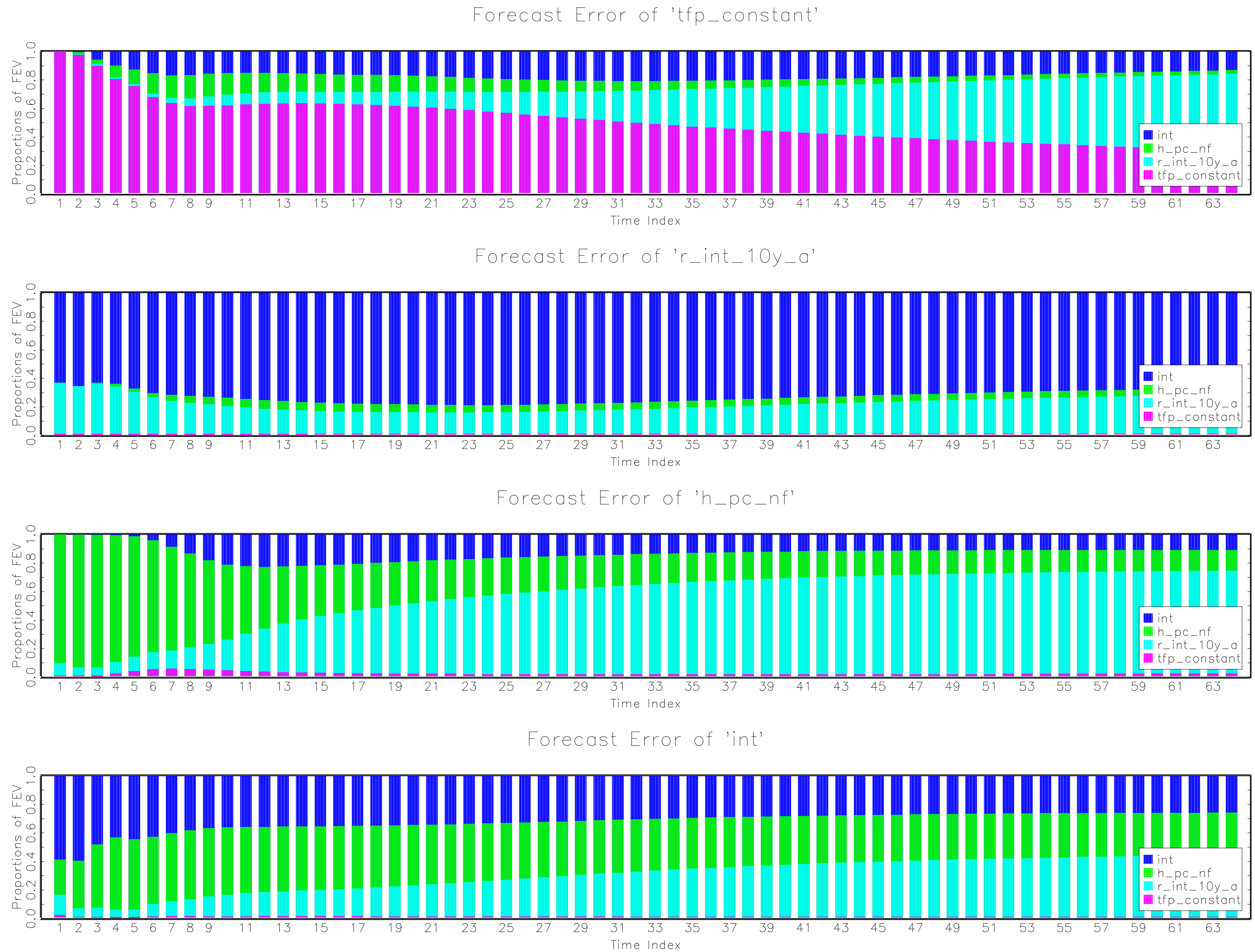

Figure 36: Long-run FEVDs of identification A with real return of 10 year treasuries, 1957Q1-1999Q1

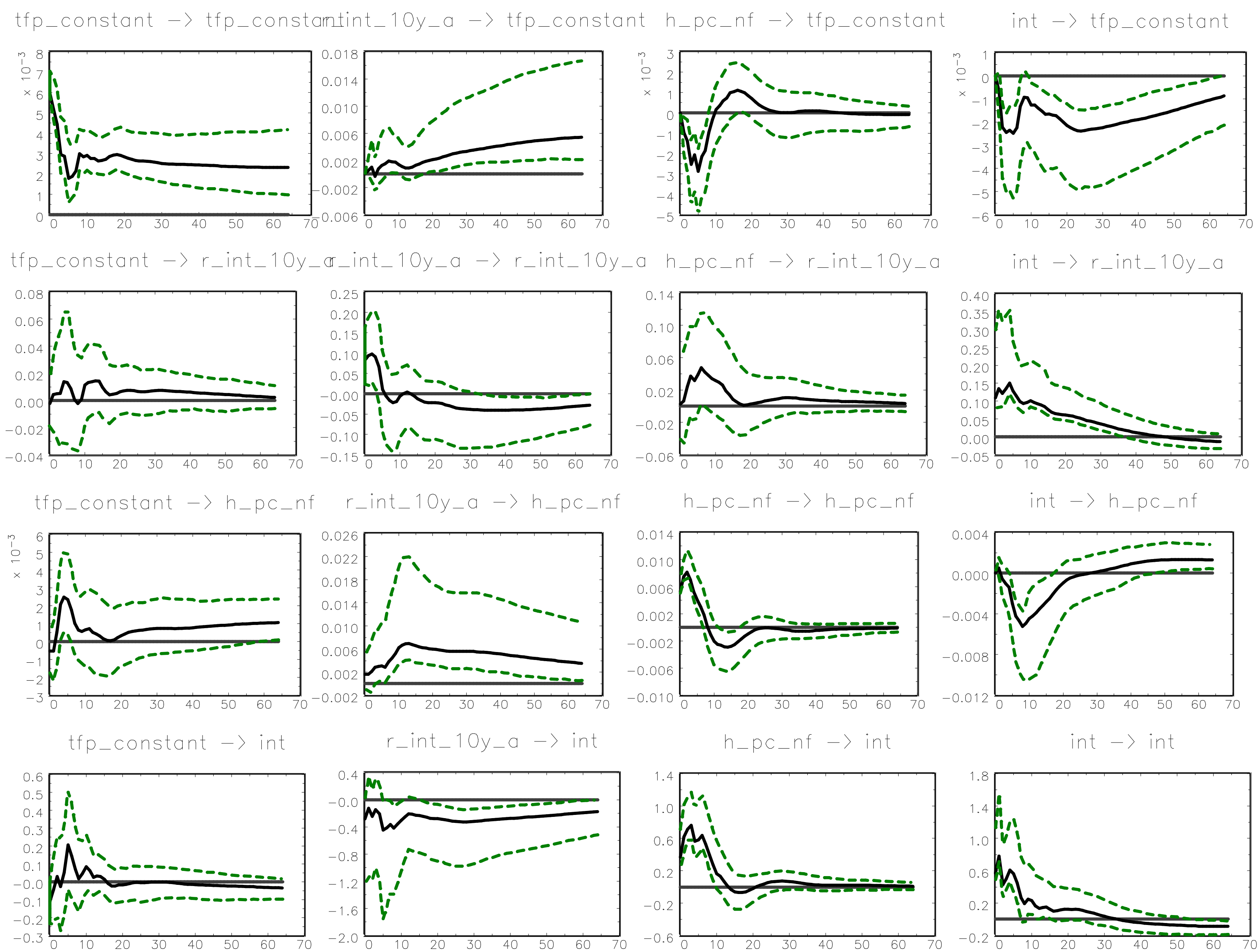

Figure 37: Long-run IRs of identification A with real return of 10 year treasuries, 1957Q1-1999Q1, dashed lines represent 95% bootstrapped Hall confidence intervals.

5.6 Data Sources and Transformations

Table 7: Data Descriptions and Transformations

Mnemonic	**Description**	**Institution**	**Source**	**Start**	**End**	T
pop_sa_q	Civilian non-institutional population, age 16 and over	BLS	CPS	1948Q1	2008Q4	3[38]
y_nf_pc	Gross Value Added nonfarm private business, real per capita	BEA	NIPA	1947Q1	2008Q4	1,3,4
KU_manu	Capital Utilization in Manufacturing	Fed	SR G.17	1947Q1	2008Q4	-
k_nf_pc	Capital Services in nonfarm private business, utility adjusted, real per capita	BLS	MFP	1948Q1	2008Q4	1,3,4
α_nf	Labor share in nonfarm private business	BLS	MFP	1947Q1	2008Q4	-
tfp_const	Total factor productivity, calculated using a constant labor share of 0.69	BLS, BEA	author's calculation	1948Q1	2008Q4	-
tfp_standard	Total factor productivity, calculated using the BLS quarterly labor share in non-farm private business	BLS, BEA	author's calculation	1948Q1	2008Q4	-

[38] 1 - divided by civilian non-institutional population, aged 16 and over, 2a - adjusted by NIPA personal consumption expenditure deflator, 2b - adjusted by NIPA nonresidential private fixed domestic investment deflator, 3 - X12 ARIMA seasonal adjustment, 4 - taking the natural logarithm, 5 - interpolated into quarterly frequency assuming constant growth rates, 6 - taking the end of quarter value, 7 - averaging over the quarter

Mnemonic	**Description**	**Institution**	**Source**	**Start**	**End**	T
tfp_tornqvist	as tfp_standard, but using instead the tornqvist specification	BLS, BEA	author's calculation	1948Q1	2008Q4	-
i_defl	Deflator of nonresidential private fixed domestic investment	BEA	NIPA	1947Q1	2008Q4	-
c_defl	Deflator of personal consumption expenditures	BEA	NIPA	1947Q1	2008Q4	-
pi	Inverse relative price of investment, log difference of c_defl and i_defl	BEA	author's calculation	1947Q1	2008Q4	4
sp_p	S&P 500 Index	Standard & Poors	Shiller	1948Q1	2008Q4	1,2,4,6
Wilshire 5000	Dow Jones Wilshire, Broad, 5000 Index (Full Cap), Total Return, Close, USD	Dow Jones	EcoWin	1970Q1	2008Q4	1,2,4,6
cmod_crb	CRB commodity spot price index	CRB	Datastream	1951Q1	2008Q4	1,2b,4,6
cmod_raw	CRB commodity spot price index for raw materials	CRB	Datastream	1951Q1	2008Q4	1,2b,4,6
oil	Crude Oil - Brent Crude, U.S. Dollar per Barrel	International Petroleum Exchange	Datastream	1948Q1	2008Q4	1,2b,4,6
prime_rate	Average majority prime rate charged by banks on short-term loans to business	Fed	SR H.15	1949Q1	2008Q4	7
int	Federal Reserve effective rate	Fed	SR H.15	1954Q3	2008Q4	7

Mnemonic	**Description**	**Institution**	**Source**	**Start**	**End**	T
r_int_3m	3-month Treasury bill secondary market rate, quoted on discount basis	Fed	SR H.15	1947Q1	2008Q4	2b,7
r_int_2y	Market yield on U.S. Treasury securities at 2-year, constant maturity, quoted on investment basis	Fed	SR H.15	1976Q2	2007Q1	2b,7
r_int_3y	Market yield on U.S. Treasury securities at 3-year, constant maturity, quoted on investment basis	Fed	SR H.15	1962Q1	2006Q1	2b,7
r_int_5y	Market yield on U.S. Treasury securities at 5-year, constant maturity, quoted on investment basis	Fed	SR H.15	1962Q1	2004Q1	2b,7
r_int_7y	Market yield on U.S. Treasury securities at 7-year, constant maturity, quoted on investment basis	Fed	SR H.15	1969Q3	2002Q1	2b,7
r_int_3y	Market yield on U.S. Treasury securities at 10-year, constant maturity, quoted on investment basis	Fed	SR H.15	1962Q1	1999Q1	2b,7
patents	U.S. patent applications with U.S. origin, utility patents only	U.S. Patent and Trademark Office	U.S. Patent and Trademark Office	1963Q1	2008Q4	4,5

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