Letting Different Views about Business Cycles Compete[1]

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Abstract: There are several candidate explanations for macro-fluctuations. Two of the most common discussed sources are surprise changes in disembodied technology and monetary innovations. Another popular explanation is found under the heading of a preference or more generally a demand shock. More recently two other explanations have been advocated: surprise changes in investment specific technology and news about future technology growth. The aim of this paper is to provide a quantitative assessment of the relative merits of all these explanations by adopting a framework which allows them to compete. In particular, we propose a co-integrated SVAR approach that encompasses all 5 shocks and thereby offers a coherent evaluation of the dynamics they induce as well as their contribution to macro volatility. Our main finding is that surprise changes in technology, whether it be of the disembodied or embodied nature, account for very little of fluctuations. In contrast, expected changes in technology appear to be an important force, with preference/demand shocks and monetary shocks also playing non-negligible roles.

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1. Introduction

The rise of real business cycle (RBC) models in the 1980s initiated much controversy about the main driving forces of macroeconomic fluctuations. Some 25 years later, the profession has still not reached a consensus on this issue. Shocks to disembodied technology had been singled out by the RBC literature as a central element in business cycle fluctuations. In contrast, a large literature based on new Keynesian models tends to emphasize instead the importance of monetary and other non-technology shocks in fluctuations. For example, an influential paper by Galí (1999) has suggested that surprise technology shocks may not be an important contributor to business cycle fluctuations. More recently, Fisher (2006) reframed the debate by distinguishing between shocks to disembodied and embodied technology. While he found the former to be unimportant indeed, he claimed that shocks to investment specific technology (IST) are the major source of hours variance. Simultaneously, Beaudry and Portier (2006) suggested expectational shocks reflecting news about future technological developments (referred to as news shocks) as an important force behind macro fluctuations.

In this paper, we aim to assess the relative importance of several candidate explanations of macroeconomic fluctuations by adopting a framework which allows them to compete. Following, among others, Galí (1999) and Fisher (2003, 2006), we use a structural vector autoregressive approach (SVAR) to explore this issue. We depart slightly from these authors by explicitly allowing for cointegration. Within this framework, we explore several alternative identification schemes that allow us to isolate five shocks commonly discussed in the literature. These are: surprise changes to disembodied and to embodied technology, news shocks, monetary policy shocks and preference shocks.

Our benchmark identification scheme imposes only a few long-run restrictions since at least three of the shocks we consider (two surprise technology shocks and the news shocks) may well cause permanent effects. The first identification scheme we propose therefore relies mostly on impact restrictions. For example, the news shock is identified to be orthogonal to measures of total factor productivity (TFP) and the relative price of investment on impact, but unrestricted in the long run. However, to illustrate the robustness of our results, we also work with an alternative identification scheme which imposes fewer short run restrictions and relies more on long-run restrictions.

Our baseline VECM model is composed of five variables: measured total factor productivity, the relative price of investment goods, an index of stock prices, hours worked, and the Fed funds rate. In accordance with much of the literature, we choose hours of work as our primary measure of aggregate economic activity. We also document the robustness of our results by considering alternative measures of economic activity such as consumption, investment and output. Following Fisher (2006), we use the relative price of investment to help identify investment specific technology (IST) shocks. Since standard deflators from the National Income and Product Accounts (NIPA) have been criticized for insufficient quality adjustment, e. g. Gordon (1989), we also work with a measure of the real price of investment based on the work of Cummins and Violante (2002) and adjust investment, output, TFP and capital stock data accordingly. We do not find that the issue of quality adjustment matters much.

Our main findings are as follows. Our two main identification schemes give very similar results. In both cases we find that neither type of surprise technology shock explains more than a small share of activity variance. The dominant force appears to be the news shock, which preceeds growth in measured TFP by about 2 years. Monetary shocks, preference shocks and in some cases surprise TFP shocks play more minor roles but are not negligible.

IST shocks, on the other hand, appear to play a negligible role in fluctuations, provided the analysis allows for the possibility of news shocks reflected in stock prices. These results are shown to be robust across various modifications of the underlying dependent variables and the identifying assumptions.

The paper is organized as follows: Section 2 presents our structural vector error correction framework (VECMs) and discusses the identifying assumptions for our two basic identification schemes. Section 3 describes the data base and Section 4 contains the analysis of the benchmark system under both identification strategies. In Section 5 we modify the system to allow for improved investment good quality adjustment. Further robustness checks are in Section 6. Here we also explore why our results differ from previous studies. Section 7 concludes.

2. Framework of the analysis

Our objective is to identify and quantify the relative importance of five shocks which we consider as important contenders for explaining business cycle fluctuations. These shocks are: surprise shocks to total factor productivity, surprise shocks to investment specific technology (IST), news about future technology, preference shocks and monetary shocks. To achieve this goal, we will work mainly with a five-variable structural vector error correction model (SVECM). Specifically, we consider an environment where a *K*-dimensional vector of observable variables y_t is integrated of order one and can be represented as a vector autoregressive (VAR) process of order $p < \infty$. Allowing for $r > 0$ co-integrating vectors, then the error-correction representation of the process is given by

$$\Delta y_t = \alpha\beta' y_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta y_{t-j} + u_t \tag{1}$$

where α and β are $K \times r$ matrices of loading coefficients and co-integrating vectors, respectively, the Γ_j's, $j = 1,..., p-1$, are $K \times K$ coefficient matrices and u_t are the reduced form error terms. These can be thought to be linear combinations of the structural shocks ε_t we are interested in. As is common in the literature, we assume that the covariance matrix of ε_t is the identity matrix I_K. Since the covariance matrix of u_t is nonsingular, there exists a nonsingular matrix B such that $u_t = B\varepsilon_t$. This matrix is not unique and suitable assumptions must be imposed on its coefficients to identify it. The structural model, a *B*-model in the sense of Lütkepohl (2005), is then obtained from (1) by applying the Granger Representation Theorem:

$$y_t = L\sum_{\tau=1}^{t-1} \varepsilon_\tau + B\varepsilon_t + \sum_{\tau=1}^{\infty} \Xi_\tau^* B\varepsilon_{t-\tau} + y^0 \tag{2}$$

where y^0 is a vector of initial conditions, $L := \beta_\perp \left[\alpha_\perp' \left(I_K - \sum_{i=1}^{p-1} \Gamma_i \right) \beta_\perp \right]^{-1} \alpha_\perp' B$ is a $K \times K$ matrix with rank *K-r*, $\alpha_\perp, \beta_\perp$ denote orthogonal complements of α, β, respectively, and the matrices Ξ_j^*, $j = 1,...,\infty$, are absolutely summable, i. e. $\lim_{\tau\to\infty} \Xi_\tau^* = 0$. Hence, in terms of structural interpretation, L is the long run multiplier matrix of the structural shocks ε_t and B is the corresponding short run impact matrix. We have to propose and justify (at least)

$K(K-1)/2$ restrictions on $B =: (b_{ij})$ and $L =: (l_{ij})$ to identify the structural shocks. Thus for $K = 5$, we need at minimum ten restrictions to identify the five structural shocks of interest[2].

Many structural models can be approximated by the type of moving average representation given in (2), e. g. most linearized stochastic dynamic general equilibrium models. To set ideas, it is useful to imagine the underlying data generating process as potentially being derived from a representative agent model where there is a final good sector and an investment good sector, and where technology in each sector is stochastic. Moreover, the representative agent in this model economy is allowed to be subject to stochastic changes in preferences. The idea of technological news in such a setting can be captured by assuming that the representative household learns about productivity innovations before they are effectively implemented in the economy (news shocks can be interpreted as diffusion lags in technology). In a web appendix (www.wiso.uni-hamburg.de/beaudry-lucke), we present an extended RBC model that incorporates all these characteristics. The illustrative model we present in that appendix is also an example of a model that satisfies the type of identification assumptions we will pursue here to recover structural shocks.

Many papers, e.g. Chari, Kehoe and McGrattan (2008), question the plausibility of structural VAR methodology being used to identify structural shocks. For this reason, in our web appendix we use artificial data generated from the structural model to explore whether the identification strategies we use in this paper are likely to allow identification. When the model is calibrated to deliver a variance decomposition similar to that observed in US data, we find that the methodology works well.

[2] Since the long-run matrix is singular, ten restrictions may not be sufficient for identification.

A priori, it is not obvious that our five shocks of interest can be identified, that is, it is not obvious that there exists a vector y with corresponding B and L matrices which exhibit 10 theoretically plausible restrictions. However, as we will show, by choosing the vector y carefully, the desired identification can be achieved quite easily by exploiting a set of properties that are common to most contemporary models embodying such shocks. In fact, we will advance two main identification schemes to isolate the shocks of interest. While these two identification schemes share some common restrictions, they will also differ considerably. Since in many models both these schemes should achieve the same identification, it is of interest to know whether their empirical implementation renders similar results. If they do lead to similar results, it will offer support to the claim that we have isolated the shocks of interest. In fact, in the robustness section we will study a broad variety of identification schemes related to the two basic settings and show that our findings are very robust across these schemes.

The five observable variables on which we will base our primary analysis are: measured Total Factor Productivity (TFP), the inverse of the relative price of investment goods, a stock market index, a measure of economic activity (such as hours worked, investment, consumption or output), and finally the rate of interest on Fed Funds. Details on the construction of the variables are discussed in the next section. Intuitively, the reasons we choose these variables are that; (i) measured TFP should help identify innovations to disembodied technology, (ii) the value of the stock market should help isolate news about future technological developments, (iii) the fed funds rate should help identify monetary policy shocks, (iv) we need a measure of economic activity since it is our main focus, and finally, (v) since the relative price of investment goods is modelled by most researchers as an indicator of investment specific technological change, it therefore is likely helpful in identifying investment specific technological shocks.[3]

Since in most of the business cycle literature TFP is considered a driving force, we will exploit this property to help identify shocks. In particular, we will begin by assuming the following properties for the relationship between TFP and the structural shocks.

Assumption A1: Only TFP shocks may have contemporaneous effects on TFP.

Assumption A2: Preference shocks and monetary shocks have no long run effects on TFP.

Without loss of generality, if we let the order of dependent variables in the vector y_t be total factor productivity, inverse of relative investment price, stock price index, activity and federal funds rate, and let the order of the structural ε_t-shocks be TFP-shock, IST-shock, news shock, preference shock and monetary shock, then Assumptions A1 and A2 imply the identifying restrictions $b_{12} = b_{13} = b_{14} = b_{15} = 0$ and $l_{14} = l_{15} = 0$, respectively.

Assumptions A1 and A2 follow directly from common assumptions regarding TFP as a driving force of economic fluctuations. In particular, it is quite natural to assume that the TFP process is independent of preference shocks and monetary shocks both in the short and long

[3] For example, Greenwood, Hercowitz and Krusell (1997) and most others model IST as different vintages of capital goods. A new vintage has the property that a more productive capital good can be produced at the resource cost of one consumption good than in previous vintages. Hence, the price of investment goods in constant (base year) quality declines over time relative to the price of consumption goods. If the capital stock K_t is measured in constant quality investment goods I_t, the capital accumulation equation is

$$K_{t+1} = \left(1-\delta\right) K_{t-1} + V_t I_t$$

where V_t is the inverse of the relative price of investment goods. Since we are interested in identifying shocks to IST, we will include the ratio of the consumer price index to an investment price index in the SVECM.

run. In addition, in the literature on IST, the process for TFP is generally modelled as independent of innovations in investment specific technological change. With respect to news about future technological change, by definition, these shocks have no impact effects on TFP (following Beaudry and Portier (2006)) or IST but are allowed to predict long run movements in tTFP. Since measured TFP may be contaminated by changes in the price of capital, we will later explore the effect of dropping the restrictions b_{12}=0.

The second identification restriction we will impose in this section is that monetary shocks affect economic activity only with delay, as stated under Assumption A3. This assumption has been widely used in the literature aimed at identifying the effects of monetary disturbances, (cf. e. g. Bagliano and Favero (1998)). Since we want to be consistent with this literature, we maintain this assumption. A3 yields the identifying restriction $b_{45} = 0$.

Assumption A3: Monetary shocks do not have a contemporaneous effect on economic activity.

Assumption A1, A2 and A3 provide seven restrictions. To identify the five shocks of interest we therefore need at least three additional restrictions. We will begin by suggesting two sets of additional restrictions. In both cases, these restrictions will exploit properties of the relative price of investment. Our first approach is to examine impact restrictions implied by the literature that incorporates investment specific technological change into macro models. In most of this literature, the final good can be transformed to investment goods using a linear technology, and it is shocks to this linear technology that are referred to as investment specific technology shocks. The market implementation of this technology implies that the relative price of investment goods in terms of consumption goods reflects the investment specific technology. Since the process for investment specific technological change is modelled as a process driven by one shock, it follows that monetary shocks, preference shocks and news shocks should have no contemporaneous effects on the relative price of investment goods. This feature is captured by Assumption B1.

Assumption B1: News shocks, preferences shocks and monetary shocks have no contemporaneous effects on the relative price of investment.

Assumption B1 implies the restrictions $b_{23} = b_{24} = b_{25} = 0$. The combination of assumptions A1, A2, A3 and B1 provides sufficient theoretical restrictions for isolating the five shocks of interest. As we shall later show, adding the restriction $b_{21} = 0$ to this system – which becomes an over-identifying restriction - is not rejected by the data and does not alter results. We will refer to the identifying scheme embodying assumptions A1, A2, A3 and B1 as ID1. The restrictions associated with ID1 are summarized below, where the set of restrictions on matrices *B* and *L* is shown explicitly.

$$B = \begin{pmatrix} * & 0 & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 \\ * & * & * & * & * \\ * & * & * & * & 0 \\ * & * & * & * & * \end{pmatrix}, \quad L = \begin{pmatrix} * & * & * & 0 & 0 \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \end{pmatrix} \tag{3}$$

Here, starred entries denote unrestricted elements of *B* and *L*. Note that under ID1 the news shock is identified by postulating zero effects on both types of technology on impact, but allowing for unrestricted long-run effects. Thus, under this identification scheme news can be news about both TFP and IST innovations. Similarly, under ID1, the notion of a preference shock can be given a far more general interpretation than the term may suggest. For example, our identification strategy is compatible with the preference shocks representing any kind of temporary non-monetary demand shocks (e. g. increases in government spending or foreign demand) or with changes in market structure (e. g. transitory changes in markups). It is also compatible with non-technology expectational shocks (e. g. socially inefficient market rushes in the sense of Beaudry, Collard and Portier (2006) or even sunspot shocks and bubbles). Thus, while we label this shock a “preference” shock, the rather weak identifying assumptions for this shock allow it to stand in for any non-monetary shock that is orthogonal to technology on impact and has no long run effect on TFP. One of the attractive features of ID1 is that it mainly relies on impact restrictions, and therefore is less likely subject to the criticism presented in Chari, McGrattan and Kehoe (2008) regarding the use of long run restrictions.

Most models which incorporate IST assume that the relative price of investment only reacts to investment specific technological shocks. Our identification scheme ID1 imposes considerably weaker restrictions e. g. the relative price of investment can react to any shock with a lag. Nevertheless, ID1 might be criticised for ruling out that news, preference or money shocks change the relative price of investment on impact. For example, if it is the case that there are adjustment costs associated with investment, then the relative price of investment may vary in the short run with any shock that increases investment. If this is the case, Assumption B1 would not be valid. For this reason, it appears desirable to search for an alternative identification scheme which is not subject to this criticism.

An alternative means to identify the shocks of interest is to drop assumption B1 and instead focus on long run restrictions that models impose on the relative price of investment. This approach is very similar to that proposed in Fisher (2006). In most of the literature incorporating investment specific technological change, investment specific shocks are the sole driver of the long run behaviour of the relative price of investment goods. This property will also hold in models where there are adjustment costs to investment and therefore is not subject to the previous criticism. Hence it is natural, at a minimum, to assume that monetary shocks and preferences shocks do not affect the relative price of investment in the long run.

Assumption C1 expresses this property. We could in addition want to impose that news and TFP shocks do not affect the long run behaviour of the relative price of investment, since this would be consistent with the idea that only IST shocks drive the long run behaviour of the relative price of investment. However, instead of imposing these additional restrictions, we will examine whether such properties are supported by the data. In particular, we want to allow news shocks to potentially contain information about future changes in the relative price of investment since there is no a priori reason to eliminate such a possibility. As for TFP shocks, we will show that the additional restriction in which TFP shocks do not affect relative price of investment in the long run is easily accepted by the data.

Assumption C1: Preference shocks and monetary shocks have no long run effects on the relative price of investment.

Assumption C1 implies the identification restrictions. $l_{24} = l_{25} = 0$. If we combine assumption A1, A2 and C1, this is insufficient to identify the 5 shocks of interest since there is nothing that differentiates a news shock from an investment specific shock. Another common long run property that characterizes investment specific shocks in most models is that such shocks do not determine the long run behaviour of TFP. This property is expressed in Assumption C2.

Assumption C2: IST shocks do not have a long run effect on TFP.

Assumption C2 implies $l_{12} = 0$. As we already noted in the parallel case of the *B*-matrix, we might also have used the analogous restriction $l_{21} = 0$ (TFP shocks do not have a long run effect on IST). We keep this in mind as an overidentifying restriction to be tested in the robustness section below.

Our second identification scheme, which we will refer to as ID2, will be comprised of Assumption A1, A2, A3, C1 and C2. Note that this identification scheme (which we will refer to as ID2) does not place any restriction on the short run behaviour of the relative price of investment and therefore is not subject to our previous criticism.

Summing up, the just identifying restrictions for ID2 are as follows:

$$B = \begin{pmatrix} * & 0 & 0 & 0 & 0 \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & 0 \\ * & * & * & * & * \end{pmatrix}, \quad L = \begin{pmatrix} * & 0 & * & 0 & 0 \\ * & * & * & 0 & 0 \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \end{pmatrix} \tag{4}$$

3. Data

We will estimate our SVECM model using quarterly data from different sources. For the economic activity variables, we use seasonally adjusted data for gross domestic product *y*, personal consumption expenditures *c* and gross private nonresidential investment *i* from the National Income and Product Accounts (NIPA) of the Bureau of Economic Analysis (BEA), Table 1.1.5. These variables are expressed in real terms using standard NIPA deflators taken from the same source (Table 1.1.9). Hours of the non-farm business sectors *h* are drawn from the US Basic Economics Database. All variables are in logs and *y*, *c*, *i* and *h* are in per capita form using civilian non-institutional population, ages 16 and over. TFP data *tfp* are constructed using data on capital services for the private non-farm business sector published by the Bureau of Labor Statistics (BLS). We multiply capital services by the capacity utilization rate in manufacturing drawn from the Federal Reserve Statistical Release G.17. For TFP construction, hours and real GDP series are also for the non-farm business sector, the latter taken from NIPA Table 1.3.5. The capital share is set at 0.31, the mean over the sample compiled by the BLS.

To check robustness, we also construct a set of quality-adjusted (QA) variables. To this end, we use quality-adjusted deflators for total investment and equipment as used in Fisher (2003, 2006). The one drawback of the quality adjusted data is that it is available only on a shorter time span. To construct a quality adjusted capital stock we use the perpetual inventory method with fixed nonresidential investment deflated by the QA deflator for total investment. This deflator results in lower estimates of real investment prior to 2000 because all capital goods are measured in constant year 2000 quality. The resulting real investment series is denoted *iq*. The capital stock starting value is taken from the private nonresidential fixed assets series published by the BEA, Table 4.1. Depreciation is set at 0.025 per quarter. We measure the real GDP series *yq* in consumption units (deflator for nondurables and services), also in the construction of QA-adjusted total factor productivity *tfpq*.

The inverse of the real price of fixed non-residential investment *pi* is the log-difference of the NIPA deflator for consumption and the respective NIPA investment price index. An alternative measure, denoted *pieq*, uses the deflator for nondurables and services consumption and for quality-adjusted equipment investment instead[4]. Real per capita stock prices *sp* are derived as the log-difference between the Standard & Poors 500 index (SP500), the population series and the NIPA consumption deflator. In the case of QA-adjusted variables we use the deflator for nondurables and services and denot this series *spq*. The short-run nominal interest rate *int* is the H15 effective rate on federal funds.

Capital services and capital stock are available only at annual frequency. They are converted to quarterly data assuming constant growth rates within each year. Stock prices and the federal funds rate were retrieved at monthly frequency from Global Insight; the quarterly values are the monthly averages. The sample size is 1955.1-2007.2 for NIPA variables and 1955.1-2000.4 for all variables which rely on the QA deflators.

4. The Benchmark System

Our first set of results is based on the five variable system consisting of *tfp*, *pi*, *sp*, an activity measure and *int*. The only deterministic series in the VAR is a constant. If the activity is *x*, we call this the NIPA_x system. Using Akaike's information criterion (AIC) to determine the appropriate lag length, six lags are recommended for NIPA_h and NIPA_c, three lags for NIPA_i and nine lags for NIPA_y. However, as Figure 1 shows, six lags seem to be a reasonable specification for all theses systems. For the sake of maximum comparability we therefore estimate all systems with six lags (i.e. five lags in differences).

Insert Figure 1 here

[4] Fisher (2003) states that the relative price of quality adjusted equipment may be a better measure of IST than the relative price of quality adjusted total investment.

Turning to cointegration properties, one might expect from theory that the NIPA systems are driven by two stochastic trends representing disembodied and investment-specific technical progress. Johansen tests for cointegration (using six lags in levels) generally give support for this conjecture, finding either evidence of two or three cointegrating vectors. As three cointegrating vectors are consistent with our prior of having two stochastic trends in the system, we will assume three cointegrating vectors in the benchmark system and consider the possibility of only two cointegrating vectors when we study robustness.

We proceed by estimating a vector error correction model (VECM) for the NIPA_h system, which will be our benchmark. We impose three cointegrating vectors and five lags in differences. Note that we do not assume that all variables in this system have a unit root. The stationarity properties of hours, in particular, has been the subject of much debate, cf. Christiano, Eichenbaum, Vigfusson (2004). These authors show that the maintained assumption on whether or not hours have a unit root implies vastly different conclusions for its response to technological innovations if VARs in differences are used. In a VECM framework, by contrast, we do not need to impose any assumptions on the stationarity properties of hours, for if hours were in fact stationary, one of the cointegrating vectors would give nonzero weight only to the hours variable, so that the level of hours affects the first differences of the other variables in the VECM via the error correction term. Of course, if hours were trend stationary, the cointegrating combination should allow for a linear trend, but the hours series we use does not seem to have a discernible trend, cf. Figure 2.

Insert Figure 2 here

a) Identification ID1

We begin by estimating a structural decomposition of the VECM[5] using identification scheme ID1. The variables are ordered as *tfp, pi, sp, h, int.* We compute impulse responses (IR) and forcast error variance decompositions (FEVD).

The FEVDs, cf. Figure 3, show the contributions of the identified structural shocks to the forecast error variances of each dependent variable over a business cycle horizon of 32 quarters. In discussing the results, we will refer to the shocks as the surprise TFP, surprise IST, news, preference and monetary shock.

The most interesting findings from the FEVDs are the following: First, surprise TFP and IST shocks contribute almost nothing to the variance of hours at all horizons. The single most important contributor to hours variance is the news shock, in our interpretation the anticipation of future technological possibilities. Only in the very short run (the first three quarters), the preference shock dominates the variance of hours. The monetary shock explains a sizable share (about 20%) of the variance of hours after two years while most of the rest (roughly 70%) is due to the news shock.

Second, stock prices are mainly driven by the news shock, accounting for roughly 80% of the variance at all horizons. Much of the remaining variance seems to be due to preference shocks. Again, it is remarkable that “fundamentals” as represented by surprise TFP and IST shocks seem to be quite unimportant for stock prices. This would be consistent with the view that most technological innovations are known before they are implemented on a scale large enough to have a significant impact on the economy. In fact, the FEVDs show that news shocks contribute up to 30% of the variance of *tfp* at business cycle horizons, and this share increases further as time goes by, for instance, it is 60% after 15 years. Since this finding is,

[5] We use the free Jmulti software, cf. www.jmulti.de.

as we will show, very robust across different modifications of our benchmark system, it seems appropriate to infer that the major component of what we label a news shock reflects information about future disembodied technology.

Third, we have a negative result for our measure of IST. The relative investment price itself seems quite disconnected from other shocks. News shocks, in particular, which might also contain information about future IST, do not play a major role in its variance, at least not to the extent they do for disembodied technical progress. We will return to this issue after having discussed the impulse responses, to which we now turn, cf. Figure 4.

Impulse responses in Figure 4 display the responses of each dependent variable row-wise with the columns representing the shocks. Responses are given for the first 32 quarters.

As can be seen in the fifth column, monetary policy shocks are found to have effects on hours similar to those documented elsewhere in the literature, with the effect setting in gradually, peaking after about two years and then phasing off back to zero.

Preference shocks (fourth column) feature positive responses of hours and interest rates for at least the first year along with a prolonged negative response of stock prices. There is a small short-run negative impact on measured TFP and an apparently long-run positive response of the IST-variable. We do not emphasize the latter, however, since this effect is quantitatively negligible, cf. the FEVD of *pi*, and - as our further analysis will show – it is one of the few features that is not robust with respect to using quality adjusted variables.

News shocks (third column) have effects very similar to those found in Beaudry and Portier (2006), although their analysis focused mainly on a bivariate system and never included information on the relative price of investment. The news shock seems to convey information about TFP growth that starts 8 to 10 quarters in the future. This shock nevertheless causes an immediate expansion in hours lasting for about ten quarters. These news shocks also appear to be associated with an increase in nominal interest rates, although this estimate is mostly not significant. Moreover, news shocks seem to have a marginally significant positive effect on IST within the first four years or so. Note that the effect of news on hours is transitory, in line with the standard assumption of hours being a stationary series. However, as we will see below, news shocks cause permanent effects on output, investment and consumption, which strongly suggests that the identified news are predominantly technological.

Surprise shocks to TFP cause a somewhat unconventional short run response for TFP itself which may indicate the presence of measurement error in the form of a rapidly mean-reverting transitory component on top of the stochastic trend. However, the most important finding in this column seems to be that TFP shocks have no significant effects on hours at all. Moreover we find that the negative initial response of hours to positive technology shocks emphasized by Galí (1999) is insignificant and even the point estimate is almost zero for the first quarters. For the three types of technology shocks (TFP, IST and news shocks) considered in this exercise, only the news shock causes a significant response of hours and this response is unambiguously positive.

Although minor in total stock price variance, IST-shocks seem to cause a positive response of stock prices. (The point estimate is positive for all business cycle frequencies and significantly so after three years.) This could be in line with higher profitability of existing firms or with successfully developing equipment producers which make it into the SP500 after a number of years.

Note that the largest responses of *tfp* are due to surprise TFP shocks in the short run and to news shocks in the long run. Further, *tfp* seems to initially decrease slightly in response to news, preference and monetary shocks. This probably indicates that these shocks require some factor usage in order to adjust to these shocks, e. g. reorganisation which is not captured by measured output. The marginally significant positive response of *tfp* to IST shocks in the long run is probably due to incomplete quality adjustment in the capital stock series.

b) Identification ID2

As noted previously, our identification scheme ID1 may be criticised for its short run restrictions on the relative price of investment. For this reason, we now turn to reporting results based on using identification scheme ID2. Recall that the rational of ID2 is that, under a long run perspective, the real price of investment is likely to be a good measure of IST. It is less clear whether this is also true for the short run, which is why ID1 may be questioned as an appropriate identification strategy.

The results of the structural decomposition obtained under ID2, where a selection is given in Figures 5 and 6, are found to be very close to those we obtained under identification ID1. In fact, a simple correlation analysis confirms that the two identification schemes yield more or less the same type of shocks: Computing the correlation matrices of the shocks retrieved from ID1 with those retrieved from ID2, we find that all diagonal elements are higher than .8 and the off-diagonal elements are – with few exceptions - small in absolute value, cf. Table 1.

Fisher (2003, 2006) expresses output and productivity in consumption units. We checked if our results hinge on using the GDP-deflator in the computation of TFP and real stock prices. Redefining these variables with either the CPI or a price index for the consumption of nondurables and services (also for *pi*) has almost no effect on the variance decomposition of hours, both under ID1 and ID2. The only major change is a smaller news shock share in TFP and a larger news shock share in *pi*. But note that TFP may be biased if total output is deflated by a consumption price index, because the output of investment goods will be understated.

Insert Table 1 here

Thus, it is not too surprising that the IRs and FEVDs of ID2 are quite similar to those of ID1. In particular the news shock always explains most of the variance of hours, followed by the preference shock. By contrast, both IST and TFP shocks are negligible for hours variance.

5. Quality Adjusted Systems

An apparent difficulty in interpretation of our first set of results is the permanently negative response of nominal interest rates to IST shocks. This response (prevalent under both ID1 and ID2) is related to the sizable share of federal funds rate variance attributable to IST shocks at long horizons, cf. Figure 3[6]. Both results are hard to explain and could be due to *pi* being an imperfect measure of IST. A possible remedy is the use of variables with improved investment quality adjustment. Moreover, it may be the case that our finding that IST shocks play little role in hours fluctuations is due to mis-measurement of the relative price of investment.

To address these issues, consistency requires some changes in the variables in order to create a quality adjusted system. In particular, the use of a QA-deflator for investment implies different quantities for investment, output and the capital stock. Hence we use the series *iq*, *yq* (in the construction of TFP) and *tfpq* as described above. We measure the inverse of the relative price of investment as the ratio of the NIPA deflator for consumption of nondurables and services divided by the quality-adjusted deflator for equipment investment *pieq*, since Fisher (2003) argues that the equipment price series might capture IST somewhat better than

[6] The FEVD is similar under ID2.

the relative price of total investment. To ensure comparability, we retain the settings of three cointegrating vectors and five lags in differences in the VECM. We begin with identification ID1.

a) Identification ID1

Results for the FEVD associated with the quality adjusted system are presented in Figure 7. Somewhat surprisingly we find that adjusting for quality in the construction of investment price changes little the results. We still have the central finding that TFP shocks and IST shocks do not explain much of hours or stock price variance. Instead, the news shock is by far the most important contributor to hours variance and it also explains up to 30% of *tfpq*-variance at the low business cycle frequencies (increasing further at longer horizons). The importance of the preference shock, while reduced in hours, has increased substantially in the variance of stock prices. The role of the monetary shock is similar to its role in the NIPA system. Note that now the IST shock explains less of the long run variance of nominal interest rates.

Turning to the impulse responses of the QA-system, cf. Figure 8, we confirm that the change from NIPA- to QA-variables does not matter much. The monetary policy impulse of hours is virtually unchanged, as is the significant long run response of TFP to news shocks. We have a strong positive response of hours to anticipated technological innovations (news) and only a minor, though now significant, negative response to surprise TFP shocks. Unlike in the NIPA_h system, news shocks cause a small positive response of the investment price variable variable over the first four years or so, but this effect, which may be due to using a variable which better captures IST, is small in terms of the variance of the relative price of investment.

There are minor changes in the responses to preference shocks, column 4 of Figure 8. The short-run response of hours to the preference shock is less pronounced. The preference shock still has a tiny positive long-run impact on the relative price of investment (denoted *pieq*)¸ but it becomes significant only after the 32 quarters depicted in Figure 8. Similarly, the negative effect on stock prices is transitory, but it takes more than 32 quarters to return to the initial level – the long-run effect is actually positive. Thus, while there are quantitative changes, the interpretation of the preference shock given for the NIPA_h system continues to hold.

b) Identification ID2

Turning to identification ID2, we obtain more or less the same results, see the selection shown in Figures 9 and 10. Under both schemes, the counterintuitive significant long run response of the nominal interest rate to IST shocks has vanished, but in its place we observe (with opposite sign) a marginally significant long run response to TFP shocks (not shown for ID2, but similar to the response in Figure 8). The news shock remains by far the most important shock for hours with the monetary shock a distant second.

We correlate the structural residuals obtained from NIPA_h under ID1 with the structural residuals from QA_h under ID2. As the QA_h sample is shorter, we only use the NIPA_h residuals up to 2000.4. Thus, we correlate residuals obtained from different samples, estimated with different variables and decomposed under different identifying assumptions. The results (cf. Table 2) show that most diagonal elements of the correlation matrix are still in the range of .8 or higher. The one exception is the correlation between the identified IST shocks, which is .6. Thus, the bottom line from our analysis with QA-variables seems to be that the usage of QA variables might have a notable impact on the identification of IST shocks – but not on much more. In particular, the finding that IST shocks appear unimportant for economic fluctuations remains unchallenged.

Insert Table 2 here

Summing up, the differences between NIPA_h and QA_h seem relatively small and even with (possibly) improved variables there is very little evidence that IST-shocks drive a substantial fraction of macroeconomic fluctuations. The most notable qualitative change in the QA-system seems to be a more plausible long-run response of the nominal interest rate to IST shocks. But as we will show below, this property can be enforced on the NIPA_h system without any essential changes elsewhere. Thus, while we continue to use QA variables in some of the robustness checks below, we prefer to work with NIPA variables as these exploit more information in terms of the time span of the available sample.

5. Robustness:

a) Other activities

We now study the robustness of our results by looking at other measures of activity in both the NIPA and the QA systems, focussing on identification ID1. (We still use QA variables here to make sure that results do not differ when activity is measured by variables which are themselves quality adjusted.) Hence, we substitute out the hours series and replace it by investment (*i* or *iq*), output (*y* or *yq*) or consumption (*c*). We use the same (ID1) identification throughout. The FEVDs of these exercises are given in Figure 11 (activities only). As in the case of hours, we see that IST shocks do not matter much – and they matter even less in QA systems than in NIPA-systems. Surprise TFP shocks rarely account for more than 10% of the variance, the exception being the variance of output where the TFP-share sometimes reaches 20-30%. The preference shock seems generally more important in NIPA-systems than in QA-systems and is basically a short-run phenomenon. The importance of the money shock is also mostly smaller in QA systems than in NIPA-systems and consumption seems to be the activity most receptive to monetary policy. The one shock which clearly dominates the FEVDs of all activity measures is the news shock with rarely less than 50% of the variance.

Selected impulse responses are given in Figure 12, where the six rows represent, from top to bottom, the systems NIPA_i, NIPA_y, NIPA_c, QA_iq, QA_yq and QA_c. TFP seems to respond to TFP shocks with much the same kind of transitory dynamics in all systems and news shock generally have a positive long-run effect on TFP in line with Beaudry and Portier (2006). For investment, output and consumption, both TFP shocks and news shocks have permanent effects, unlike the responses for hours in either the NIPA or QA system. These permanent effects strongly suggest that news shocks are essentially technological. Recall that the identification would, in principle, also be compatible with non-technological news or sunspot shocks, but given the estimated impulse responses such an interpretation seems hard to support.

The preference shock on activity is generally more pronounced in the NIPA systems than in the QA systems. Its effect on activity is clearly transitory. Note that neither the long run effects of news shocks nor those of preference shocks are imposed through the identifying assumptions. The responses of activity to monetary shocks are very similar in all systems.

All activities display a gradual increase over a year or so in response to a news shock. Clearly, this cannot be attributed to standard factor adjustment costs, because the response of activity to a preference shock is an instantaneous jump. In fact, this difference in the initial responses seems to be an interesting distinguishing feature of news and preference shocks. It can support the interpretation of news shocks as an expectational variable, because news about future technological developments may well at first be skeptically received by many agents but a few particularly dynamic or risk-loving entrepreneurs. Thus, there may be some sort of sluggishness in the adjustment of expectations responsible for the shape of the responses to news shocks, while behavioral changes or changes in the economic environment captured by our notion of a preference shock cause an instantaneous response of activity.

b) Two cointegrating vectors

As an additional robustness check we examine what happens if we change assumptions about co-integration. When we estimate the baseline NIPA_h system with only two cointegrating vectors, the results are mostly similar to the case of three cointegrating vectors. This is true for both identification schemes. The most notable change is the impulse response of hours to the monetary shock, which now seems to have a persistent effect, cf. Figure 13 for ID1. This is also clearly visible in the variance decomposition of hours. As this is not in line with standard theory, we do not follow this approach further. The QA_h system with two cointegrating vectors has similar properties.

Insert Figure 13 here

c) Overidentifying restrictions

Up to now we have not imposed any over-identifying restrictions in our estimating procedure. Here we examine the effects of imposing such restrictions. For example, identification ID1 did not impose the restriction $b_{21} = 0$, which is a natural counterpart to the restriction $b_{12} = 0$ implied by Assumption A1. We therefore proceed by subjecting the NIPA_h system to identification scheme ID1 and the additional restriction $b_{21} = 0$. We find that the P-value of the likelihood-ratio (LR) statistic for over-identifying restrictions is 0.081, thus the restriction can be reasonably accepted. More importantly, we find that when imposing the additional restriction there are almost no changes in the estimated FEVDs and IRs.

Identification ID2 did not impose the restriction $l_{21} = 0$, which is the natural counterpart to the restriction $l_{12} = 0$ implied by Assumption C2. Overidentifying the NIPA_h system with ID2 and the additional restriction $l_{21} = 0$, we find a P-value of the LR statistic of 0.67, so this restriction is easily accepted. There are again no noteworthy changes in the IRs and FEVDs when this restriction is imposed.

We also explored the imposition of the overidentifying restriction $l_{52} = 0$ on ID1, i. e. a restriction aimed at eliminating the counterintuitive permanent effect of IST shocks on the

Federal Funds rate[7]. This restriction is clearly rejected by the LR-test. If, however, we ignore the test result and estimate the structural decomposition nonetheless, we again get results very close to those in Figures 3 and 4. Even the response of *int* to IST-shocks does not change by much during the first 32 quarters, i. e. the enforced convergence back to zero is quite slow.

d) Short-run response of hours to monetary policy

To help identify the monetary shock we assumed that activity does not respond on impact to monetary policy, i. e. $b_{45} = 0$ (Assumption A3). We here replace this restriction in ID1 by the long-run restriction $l_{25} = 0$. i. e. monetary policy does not affect IST in the long run. In the case of three cointegrating vectors the two long-run restrictions $l_{15} = l_{25} = 0$ immediately imply that the monetary shock is a transitory shock, i. e. all elements in the last column of *L* are zero (with probability one). We find that computing the structural decomposition under this alternative assumption does not change our benchmark results in any remarkable way.[8] We therefore continue to use the $b_{45} = 0$ restriction in the following exercise.

e) No restrictions on IST shocks.

So far, our results suggest that IST shocks are not very important for business cycle fluctuations. Given that this finding may be contentious, we thus explore an alternative identification scheme where we take care not to put any restrictions on the IST shock, neither in the short nor in the long run. Moreover, the relative price of investment may react on impact to any shock. Rather, identification is achieved by adopting the assumption that in the long run only IST shocks affect IST.

[7] It is not possible to over-identify ID2 with this restriction.
[8] In the case of two cointegrating vectors (i. e. with nonzero elements in the last column of *L*) the only noteworthy difference is, again, the permanent effect of monetary policy on activity, cf. Figure 13.

We call this scheme identification ID3, its restrictions are conveniently summarized in (5). Note that news shocks are taken to be news with respect to TFP, but not to IST. Thus, if there are, in fact, IST-specific news then identification ID3 will project these shocks onto the IST shock since this is the only shock with a long run effect on IST. In our opinion, ID3 is an identification strategy that is very unlikely to be biased against finding IST shocks to be the important if this is actually the case.

$$B = \begin{pmatrix} * & * & 0 & 0 & 0 \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & 0 \\ * & * & * & * & * \end{pmatrix}, \quad L = \begin{pmatrix} * & * & * & 0 & 0 \\ 0 & * & 0 & 0 & 0 \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \end{pmatrix} \tag{5}$$

Yet the results of this structural decomposition for NIPA_h (a selection is given in Figures 14 and 15) are very close to those we obtained under the benchmark identification ID1. In fact, computing the correlation matrices of the shocks retrieved from ID1 with those retrieved from ID3, we find the diagonal elements are mostly around .9 or higher and the off-diagonal elements are mostly small in absolute value, cf. Table 3.

Insert Table 3 here

f) Explaining Fisher (2003, 2006)

Our results stand in remarkable contrast to the findings of Fisher (2003, 2006) who suggested that investment-specific technical change explains a lot of hours variance. His benchmark system is a VAR in the growth rate of the relative (QA) equipment price, the growth rate of labor productivity and the level of hours. Fisher uses a Blanchard-Quah (1989) approach which relies exclusively on long-run restrictions. He imposes that only IST shocks affect IST in the long run and only IST shocks or neutral technology shocks affect labor productivity in the long run. Our identification scheme ID3 is very similar in spirit to that of Fisher as it imposes no restrictions on the IST shock, and it imposes that the investment specific shock is the only shock that drives the relative price of investment in the long run.

To try to understand the difference between our results and those of Fisher, we move to a four-dimensional system (denoted NIPA4_pi) by eliminating stock prices. In line with Johansen tests, we assume two cointegrating vectors, i. e. we allow for two stochastic trends – likely trends associated with the two technology processes. Identification is achieved by eliminating the third column and row from both *B* and *L* in ID3 and by allowing for $l_{24} \neq 0$, cf. (6).[9] As before, this identification is very close to Fisher's. It is slightly overidentified in order to make it as similar as possible to the previous identification scheme ID3.

[9] Removing only the third row and column from *B* and *L* in (5) results in an invalid set of identifying restrictions, because the number of independent restrictions for any shock must be smaller than the dimension of the system, cf. Lucke (2008), Proposition 2. By lifting $l_{24} = 0$ we ensure that this condition is satisfied for the money shock.

$$B = \begin{pmatrix} * & * & 0 & 0 \\ * & * & * & * \\ * & * & * & 0 \\ * & * & * & * \end{pmatrix} \quad L = \begin{pmatrix} * & * & 0 & 0 \\ 0 & * & 0 & * \\ * & * & * & * \\ * & * & * & * \end{pmatrix} \tag{6}$$

The results for this decomposition, see Figures 16 and 17, are very different from what we obtained so far. If we mechanically use the labels TFP shock, IST shock, preference shock and monetary shock—dropping any reference to news shocks—we find that "surprise IST" shock explains roughly 60% of hours variance across all horizons - which is more or less Fisher's finding. This shock also accounts for an increasing share of TFP variance as time goes by, both qualitatively and quantitatively in much the same way as the news shock did in the five-dimensional systems. It thus seems to be the case that the news shock, which cannot be distinguished from an IST shock in this four variable system, is mostly being picked up by the shock associated with the second column in (6).

To investigate this conjecture we compute the correlations between this "surprise IST" shock and the structural residuals in NIPA_h under benchmark identification ID1. The highest correlations are found with the NIPA_h IST shock (0.61) and the NIPA_h news shock (0.45)[10] – and they are of almost the same order of magnitude. Thus under identification (6) it seems that both the former IST shock and the former news shock are projected on the second column and this explains the higher explanatory power of IST shocks in Fisher-type identification schemes. However, if IST shocks and news shocks are allowed to compete, as in our approach, the IST shock is completely marginalized.

[10] There are also nonzero correlations with the NIPA_h preference (0.40) and money shocks (-0.39). The correlation with the NIPA_h surprise TFP shock is essentially zero (-0.03).

g) Eliminating the relative price of investment

Our analysis suggests that the relative price of investment does not add much to the explanation of macroeconomic fluctuations. We therefore explore how our results change when we drop the relative investment price. (We continue to use standard NIPA concepts and denote this system NIPA4_sp). The identification in this system is analogous to the five-dimensional case, as we only need to rely on assumptions A1, A2 and A3, as seen in (7) where the restrictions on *B* and *L* are made explicit:

$$B = \begin{pmatrix} * & 0 & 0 & 0 \\ * & * & * & * \\ * & * & * & 0 \\ * & * & * & * \end{pmatrix} \quad L = \begin{pmatrix} * & * & 0 & 0 \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{pmatrix} \qquad (7)$$

Since the relative price of investment seemed to represent a stochastic trend of minor importance for the other variables, we retain the assumption of three cointegrating vectors and estimate the VECM again in five lags in differences[11]. The variance decompositions of TFP and hours are given in Figure 18 and a selection of the resulting impulse responses (corresponding to those in Figure 12) is given in Figure 19. There is no essential change to the results in the five-dimensional system, except a somewhat greater share of preference shocks

[11] A Johansen test of less than three cointegrating vectors has a rather inconclusive P-value of 0.07.

in the variances of TFP and hours across all horizons. We again conclude that IST-shocks appear rather inessential for business cycle analysis.

h) The role of stock prices

Given the seemingly highly important role of news shocks for macroeconomic fluctuations one might argue that it should be possible to replace the stock price variable used in our analysis by any other macroeconomic variable which responds on impact to the news shock. For instance, if consumption behaviour is a rapidly adjusting forward-looking variable as postulated by standard theory, then consumption should well be suited to replace stock prices in our system. We thus examine this conjecture by estimating a four-dimensional system (denoted NIPA4_c) with consumption replacing stock prices as the second variable. The results, cf. Figures 20 and 21, seem to confirm our conjecture, the only apparent difference being that the money shock response of hours is not significant any more.

A closer analysis, however, reveals that this approach is only moderately successful. The correlation of the suspected news shock extracted from this system with the news shock from NIPA_h is a mere 0.47. While this is clearly more than its correlations with the TFP-, IFP- and preference shocks from NIPA_h (which are all zero), its correlation with the NIPA_h monetary shock is -0.67. This and the fact that the response of hours to the monetary shock is not significant in this system indicates that the decomposition may project part of the monetary shock on news, i. e. the system may have more trouble extracting news correctly from consumption that for stock prices. This may not be too surprising in view of the vastly different degree of attention real-world consumers and stock market traders typically pay to news about technological advances. The TFP shock, on the other hand, seems to be correctly identified – its correlation with its NIPA_h analogue is 0.95. As such it is interesting to see that TFP shocks explain only a negligible share of hours variance – and mostly less than 10% of the variance of consumption. The combined news/monetary shock clearly dominates the variance of consumption across all horizons, and plays an important role in hours variance as well. It still contains a substantial amount of information about future disembodied technology (cf. the variance decomposition of *tfp*) and causes responses from *tfp* and hours in much the same way as in the NIPA_h system.

i) Robustness with respect to identifying assumptions

Finally, we want to check the robustness of our results for the (five-dimensional) benchmark NIPA_h system with respect to a more systematic exploration of "reasonable" identifying assumptions where ID1, ID2 and ID3 can be seen as special cases. In particular we want to perform this exercise to illustrate that our results are not knife edge. The intersection of the three sets of identifying assumption used to this point is given by the restrictions *R*: $b_{13} = b_{14} = b_{15} = b_{45} = l_{14} = l_{15} = 0$. Moreover, we always use either restrictions R^s : $b_{24} = b_{25} = 0$ or R^l : $l_{24} = l_{25} = 0$ to express the idea that *pi* is a technology process. Thus we have essentially two basic sets of identifying restrictions, $R_1 := R \cup R^s$ and $R_2 := R \cup R^l$, each of which comprises eight restrictions. Just identification requires two additional restrictions. In principle, the logic we have used to this point(based on the structure of standard macro-models) suggests that one should be able to use any two of the following six restrictions in set *A* to identify the shocks of interest, where *A*: $b_{12} = b_{21} = b_{23} = l_{12} = l_{21} = l_{23} = 0$. Note that ID1, ID2 and ID3 are all based on using restrictions from this set.

There are 15 different pairs of restrictions in A which can be added to R_1 or R_2 to achieve identification. We will study each of these cases. This gives 30 different identification schemes (among them ID1, ID2, and ID3). Not all of these schemes actually achieve identification, since in some cases e. g. the rank condition for local identification can be violated, cf. Lütkepohl (2005, proposition 9.4). But most schemes work and we summarize the results by reporting the shares of hours variance at 8 quarters explained by the two surprise technology shocks and the news shock, cf. Table 4.

It turns out that 24 of the 30 possible sets of restrictions are sufficient for identification, with 22 of these schemes delivering very similar results as those found so far in terms of FEVDs and impulse responses. In particular, the third shock in the system, which we interpret as news shock, is found to be of major importance for hours variance (around 60%), while the first two shocks, interpreted as surprise technology shocks, are not (less than 10%). In all cases, we find that the monetary and the preference shock combined account for about 30% of fluctuations. For two identifications, however, it is the second shock which is dominating hours variance. These two cases have in common that they both use the restrictions $b_{21} = l_{21} = 0$, which imply that TFP-shocks are orthogonal to *pi* on impact and in the long run. This result may appear to suggest that IST should not be dismissed too quickly as a potentially important source of fluctuations. However, a closer look suggests that this is likely the wrong inference. First, let us note that under these two identification schemes, it is the third shock which dominates the variance of *pi* at all frequencies and not the second shock. This suggests that the third shock may more appropriately be considered the IST shock. Furthermore, we find that the impulse response associated with the second shock in these two cases looks almost identical to that we were previously calling the news shock. In particular, the impulse responses indicate that following an innovation in the second shock, TFP does not change much for about 8 quarters and then starts growing for several periods. This is precisely the type of pattern we view as being associated with the news shock. The only difference in these impulse responses and those that we previously interpreted as reflecting a news shock is that in these two cases measured TFP falls slightly following an innovation in the second shock (although the effect is not significant). Thus it seems unreasonable to interpret the second shock in these two cases as representing an IST shock. Instead, we view the two identification schemes based on $b_{21} = l_{21} = 0$ as having difficulty properly separating an IST shock and a news shock since the only restriction imposed to separate them in this case is $b_{12} = 0$. However, there is no a priori reason not to believe that both the IST shock and the news shock should have no contemporaneous effect on TFP, which explains why this identification scheme should be ruled out.

Insert Table 4 here

6. Conclusions

The main driving forces behind macroeconomic fluctuations remain the subject of much debate. After decades of research, not even a consensus on the relative importance of technological versus non-technological shocks has emerged. In a structural vector error correction exercise designed as a horserace between several main contenders we find a surprisingly clear result: Technology matters a lot, but it is expected rather than surprise technological progress which drives activity.

In fact, the joint contribution of surprise technology shocks to measures of TFP and IST rarely exceeds 20% of the variance of hours, investment or consumption. News shocks, however, often account for variance shares exceeding 50% of activity variance and generate patterns in impulse responses and variance decompositions which strongly suggest they are essentially technological.

This result is obtained under identification schemes where news shocks have to satisfy more restrictions than the surprise TFP shocks or the investment specific shocks. Thus, if anything, the horserace seems biased against news shocks. Nevertheless, news shocks not only emerge as more important, they essentially marginalize surprise technology shocks. This result is robust across many possible modifications in terms of specification and identification. Previous results in the literature which emphasized the importance of surprise technology shocks seem to be due to an identification strategy which does not include news shocks and does not include stock prices which reveal information about expectations .

In the short run, the second-most important shock is often what we call a preference shock. This shock has mostly transitory effects, e. g. increases in activity and interest rates and decreases in stock prices and, possibly, measured TFP. It may be well explained by a transitory change in consumer demand which stimulates competition. We hasten to add that similar effects might be caused by changes in the economic environment (e. g. deregulation or globalization) rather than preference shocks. The evidence we have on this shock may be compatible with various interpretations. At least some of them can be mapped on a transitory change in a preference parameter and only in this broad sense do we state that preference shocks matter for the short-run dynamics of investment and other activities.

Since money shocks are also found to explain a minor, but not negligible share of business cycle variances, our main finding is one of four relevant macroeconomic shocks: Expectation shocks on future TFP as the main driving force along with smaller roles for preference shocks, monetary shocks and - particularly in the case of output - surprise TFP-shocks. As such, it seems not advisable to reduce structural business cycle analysis to systems of dimension three or lower as this would make it impossible to properly disentangle the main shocks and analyze their propagation mechanisms.

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Figure 1

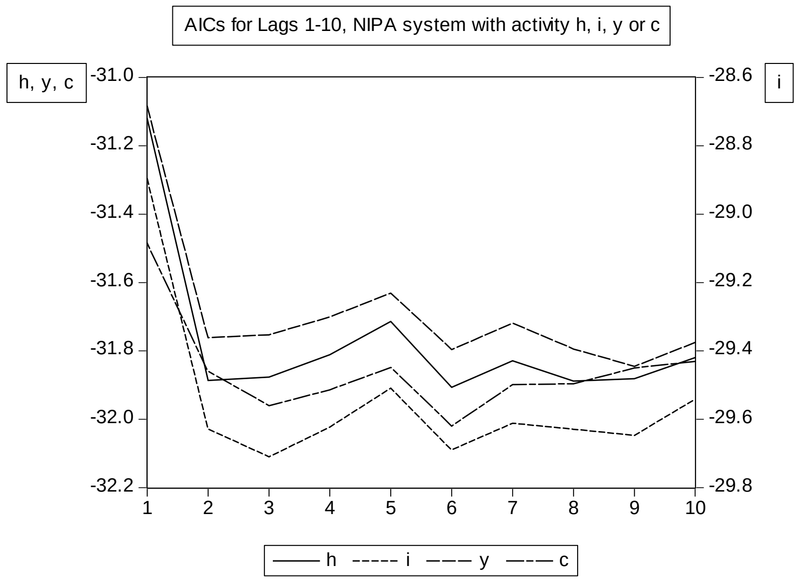

AICs for Lags 1-10, NIPA system with activity h, i, y or c
h, y, c
i
-31.0
-31.2
-31.4
-31.6
-31.8
-32.0
-32.2
-28.6
-28.8
-29.0
-29.2
-29.4
-29.6
-29.8
1
2
3
4
5
6
7
8
9
10
h
i
y
c

Figure 2

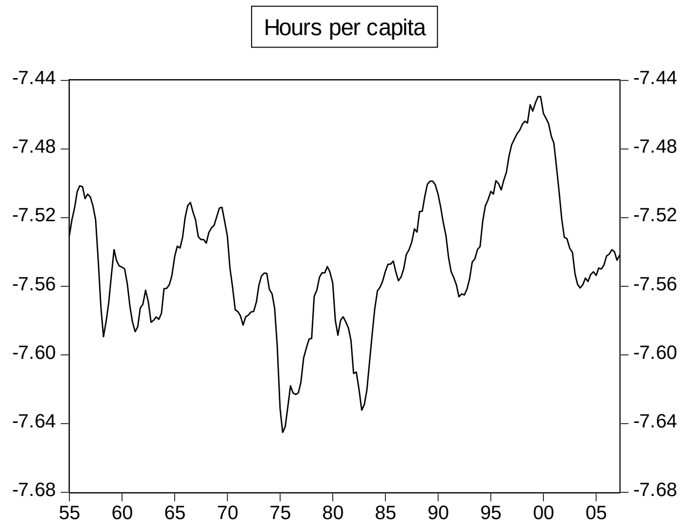
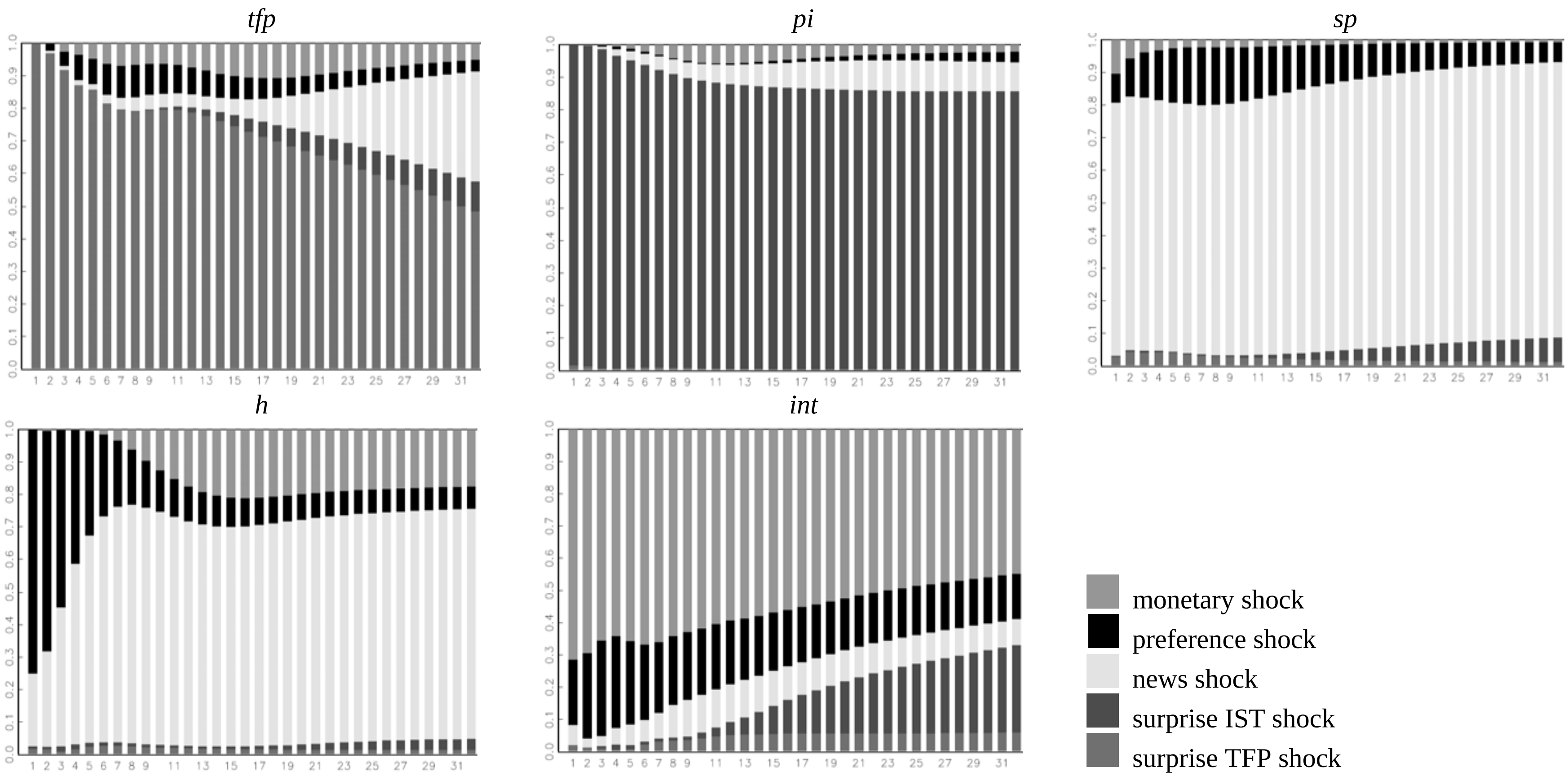
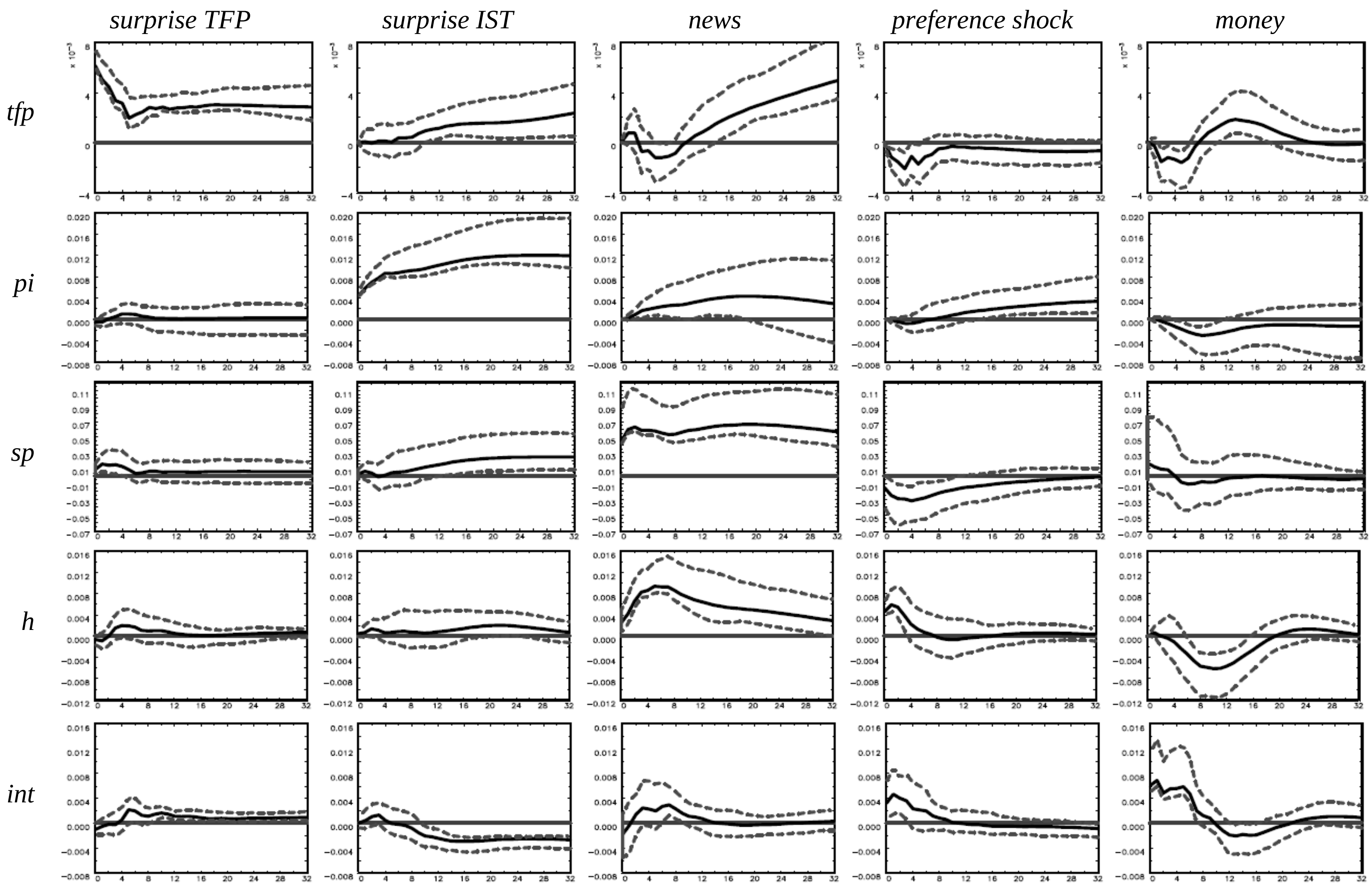

Hours per capita
-7.44
-7.48
-7.52
-7.56
-7.60
-7.64
-7.68
55
60
65
70
75
80
85
90
95
00
05

Figure 3
FEVDs of the NIPA_h System, identification ID1



tfp *pi* *sp*

Figure 4: Impulse responses of NIPA_h, identification ID1



Impulses are given in columns, responding variables in rows. Solid lines are estimated impulse responses, dashed are two standard errors bootstrapped confidence intervalls (Hall)

Figure 5: FEVDs for NIPA_h, identification ID2

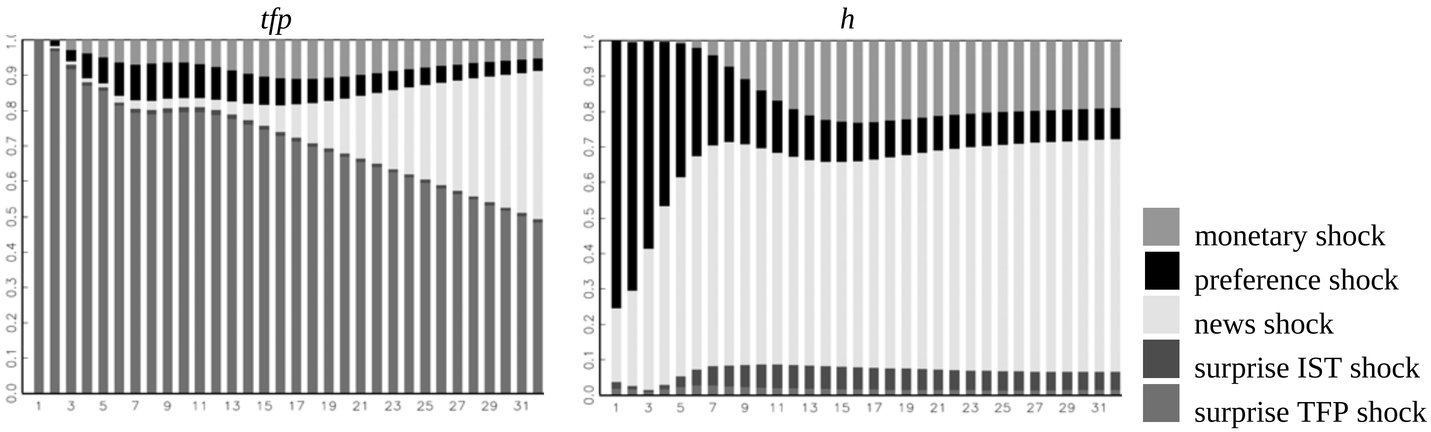


Figure 6: Impulse Responses for NIPA_h, identification ID2

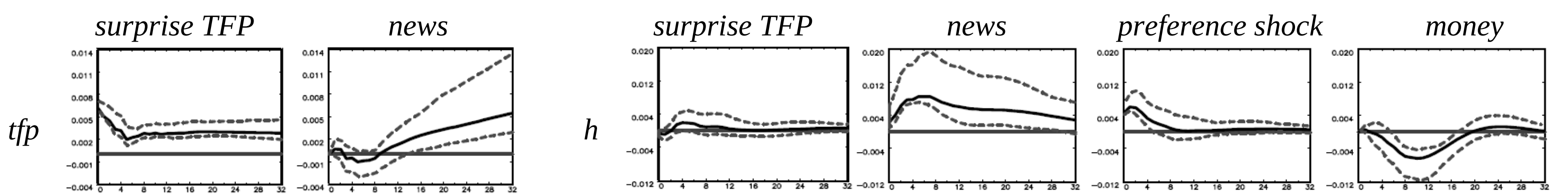


Table 1
Correlation Matrix for NIPA_h Shocks Identified by ID1 and ID2

	Shocks identified by ID2				
	1.00	0.00	0.00	0.00	0.00
Shocks	0.00	0.82	0.49	-0.29	0.07
identified by	0.00	-0.46	0.87	0.16	-0.04
ID1	0.00	0.33	0.00	0.94	0.01
	0.00	-0.08	0.00	0.01	1.00

Figure 7
FEVDs of the QA_h System, identification ID1

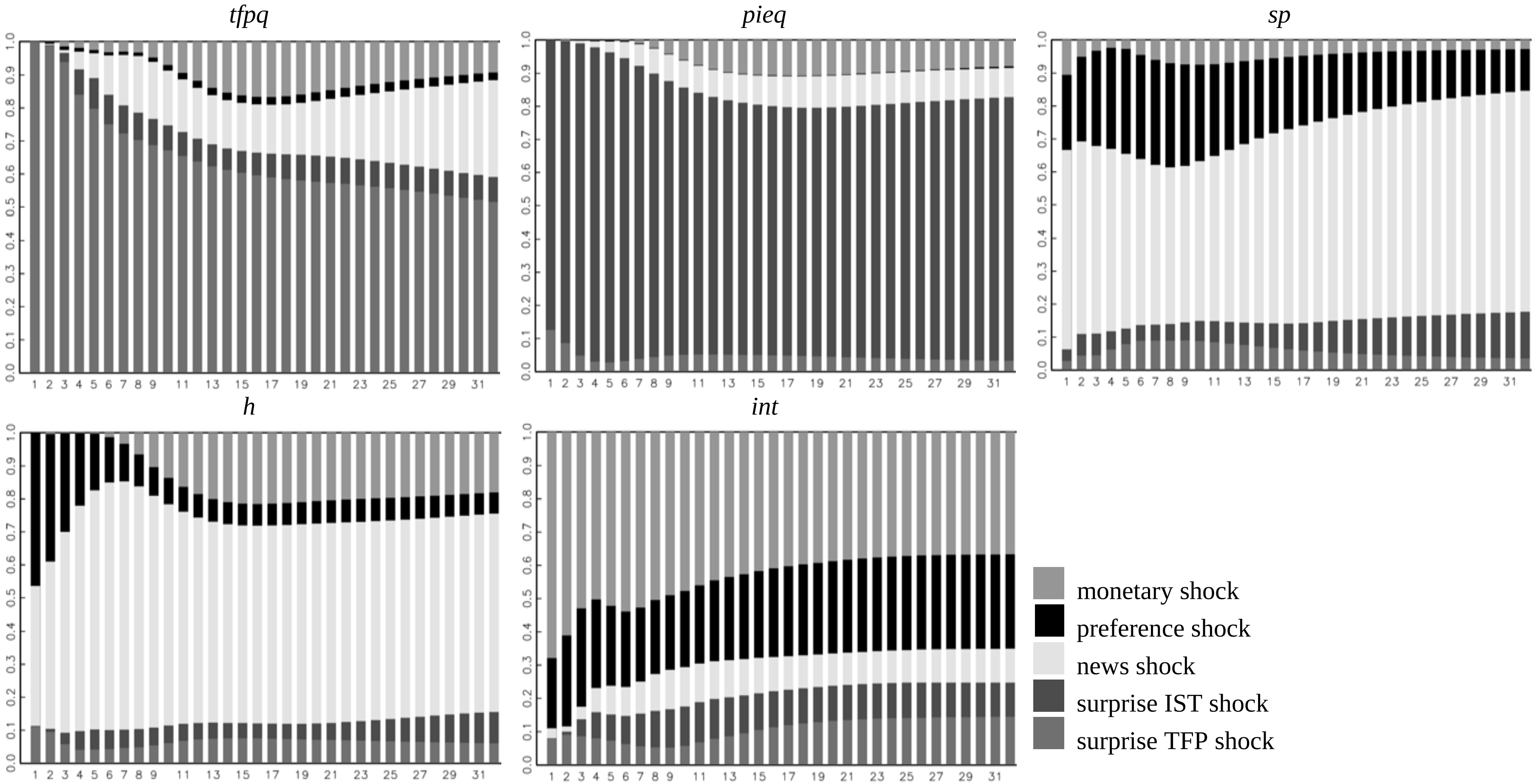
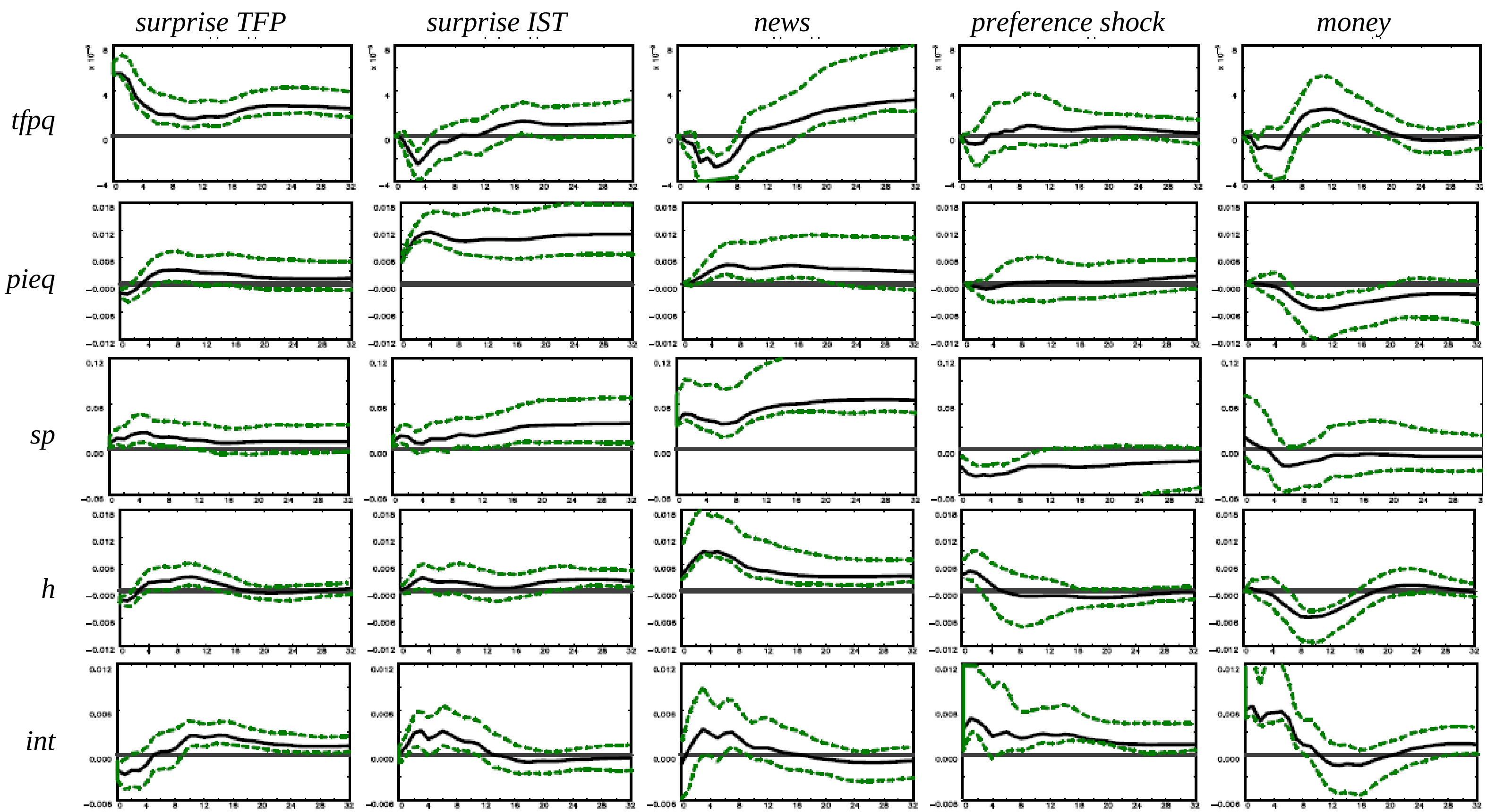


Figure 8: Impulse responses of QA_h, identification ID1



Impulses are given in columns, responding variables in rows. Solid lines are estimated impulse responses, dashed are two standard errors bootstrapped confidence intervalls (Hall)

Table 2
Correlation Matrix for NIPA_h Shocks Identified by ID1 and QA_h Shocks Identified by ID2

	QA_h Shocks identified by ID2				
NIPA_h Shocks identified by ID1	0.82	-0.11	0.12	0.16	0.04
	-0.19	0.60	0.30	-0.33	0.04
	-0.04	-0.36	0.89	-0.05	-0.04
	-0.22	0.26	0.21	0.88	0.03
	-0.09	-0.04	-0.02	-0.02	0.94

Figure 9: FEVDs for QA_h, identification ID2

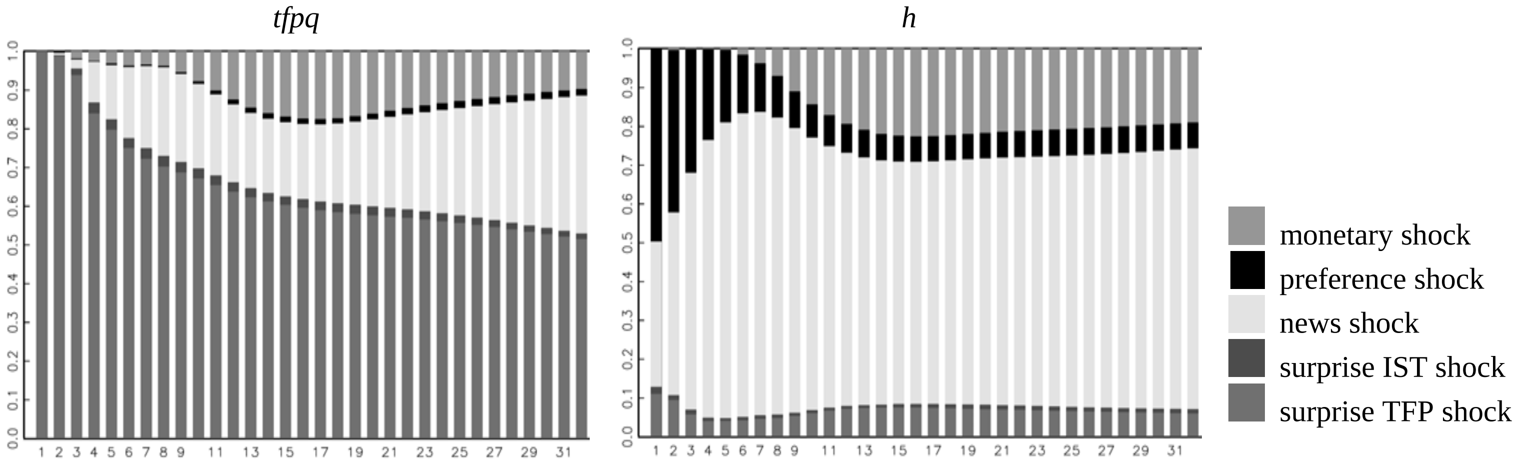


Figure 10: Impulse Responses for QA_h, identification ID2

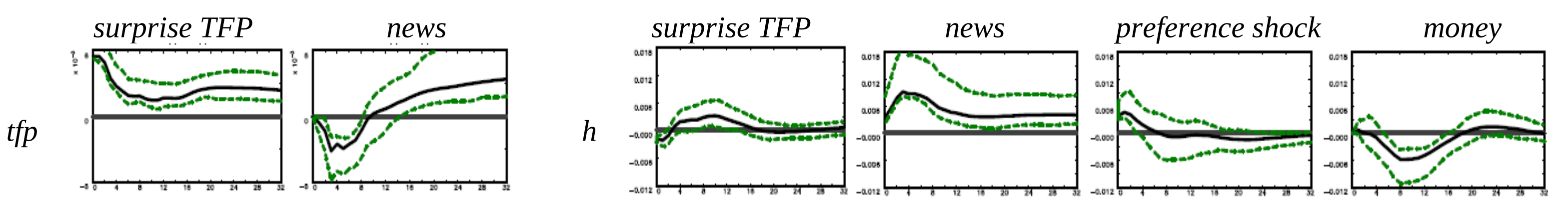
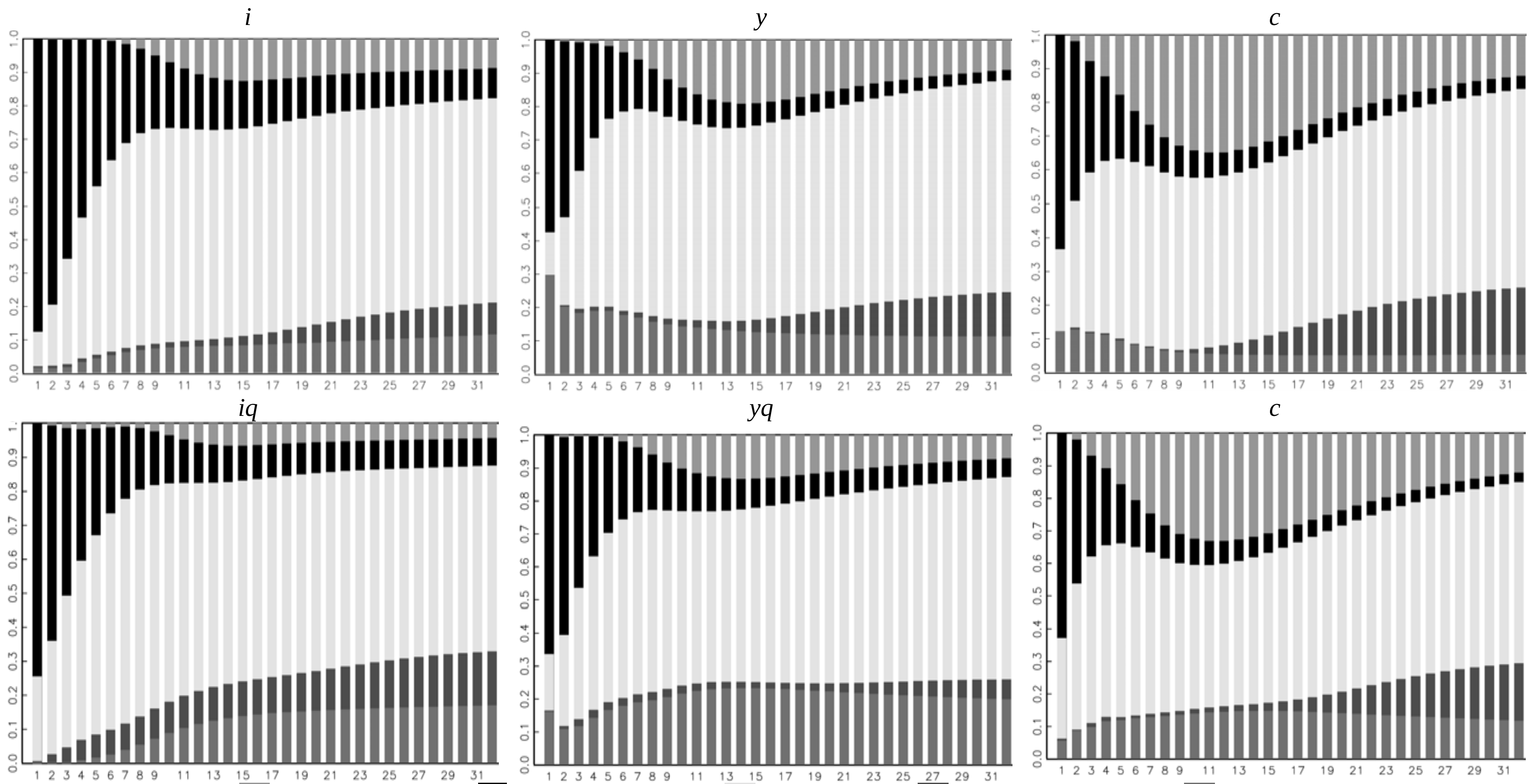
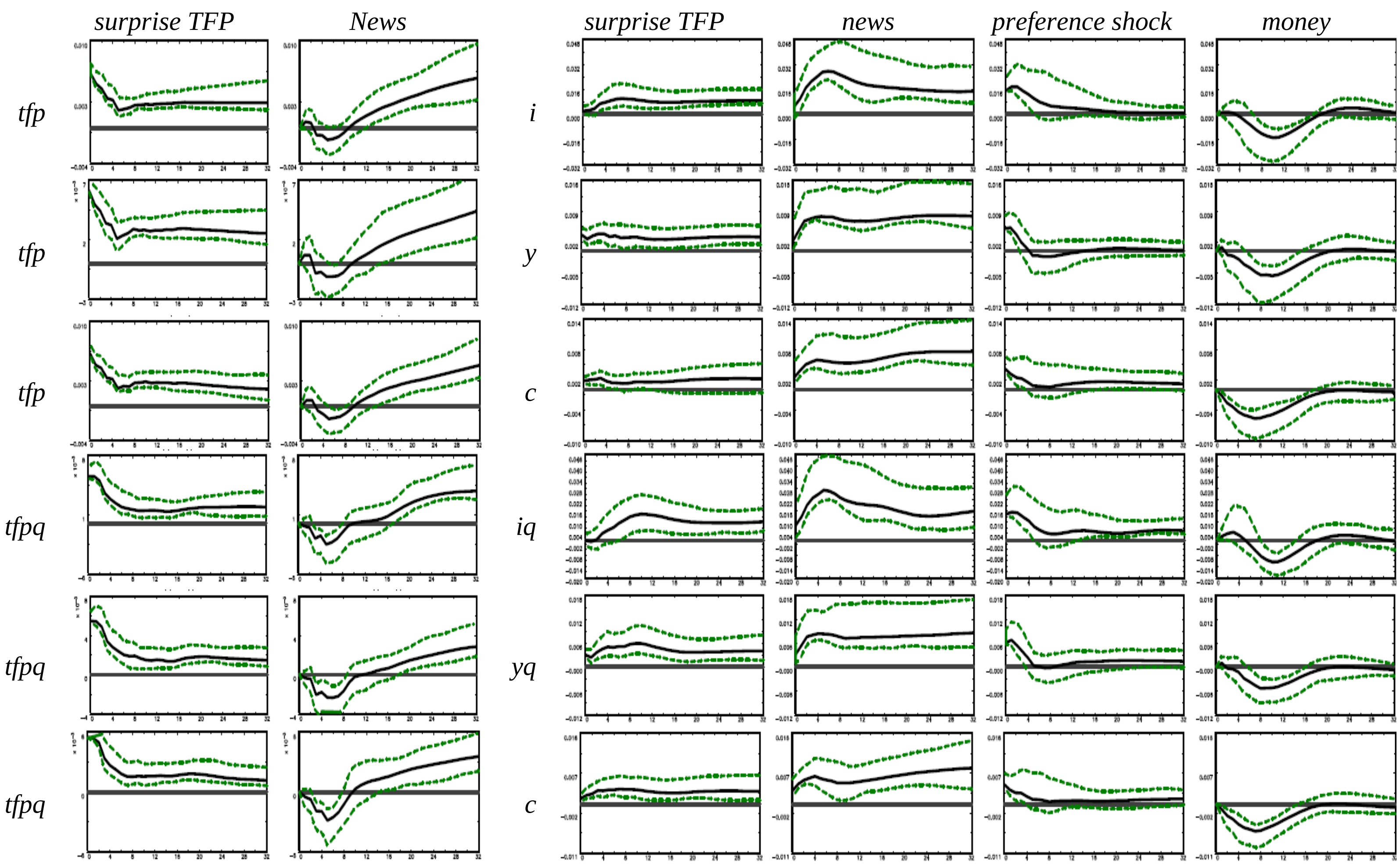


Figure 11
FEVDs of activities in NIPA systems (top panel) and QA systems (bottom panel) , identification ID1



top of bar to bottom: monetary shock preference shock news shock surprise IST shock surprise TFP shock

Figure 12: Selected Impulse Responses for NIPA_i, NIPA_y, NIPA_c, QA_iq, QA_yq, QA_c (top to bottom rows), identification ID1
Responses of TFP (left) and Activities (right)



Impulses are given in columns, responding variables in rows. Solid lines are estimated impulse responses, dashed are two standard errors bootstrapped confidence intervalls (Hall)

Figure 13
NIPA_h estimated with two cointegrating vectors, identification ID1

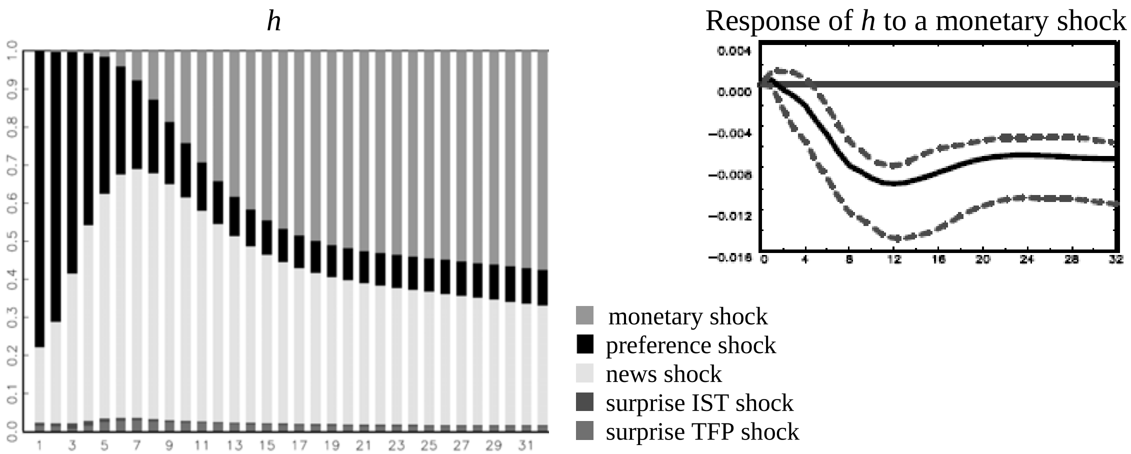


Table 3
Correlation Matrix for NIPA_h Shocks Identified by ID1 and ID3

	Shocks identified by ID3				
Shocks identified by ID1	1.00	-0.03	0.01	-0.01	0.00
	0.03	0.88	-0.33	0.33	-0.08
	0.00	0.37	0.93	-0.05	0.01
	0.00	-0.29	0.16	0.94	0.01
	0.00	0.07	-0.04	0.01	1.00

Figure 14: FEVDs for NIPA_h, identification ID3

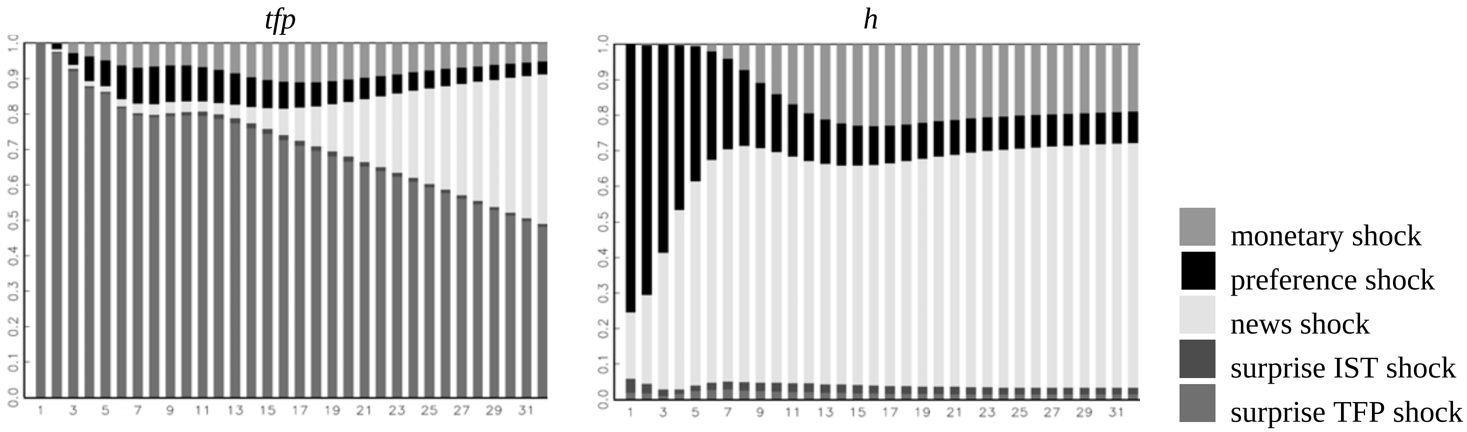


Figure 15: Impulse Responses for NIPA_h, identification ID3

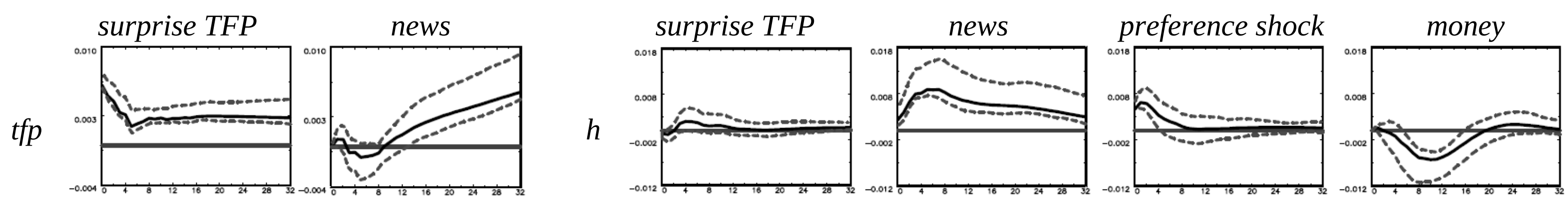


Figure 16: FEVDs for NIPA4_pi under identification **Error! Reference source not found.**

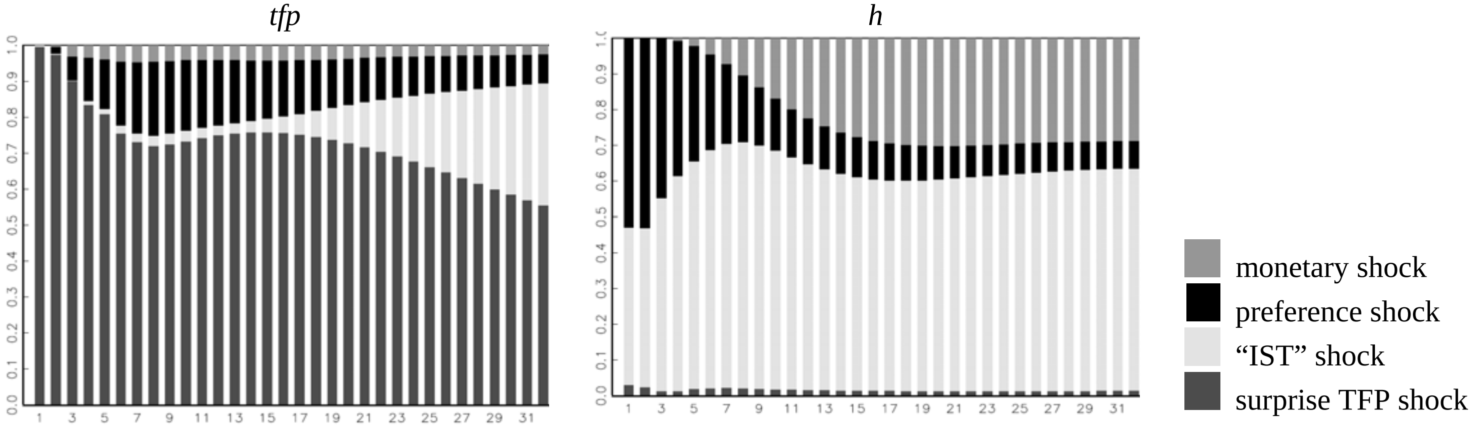
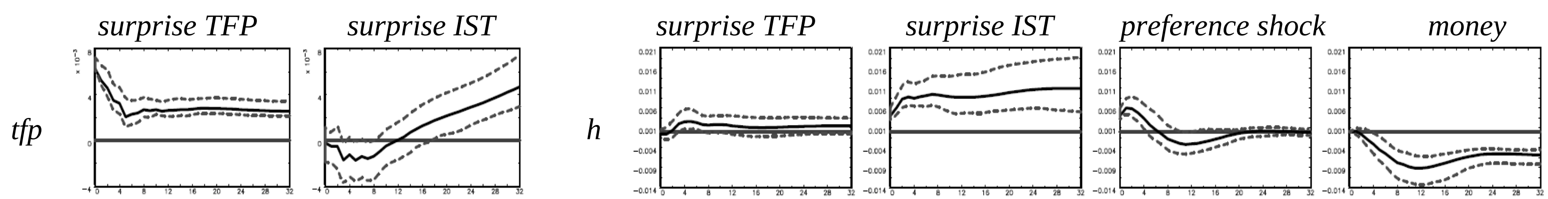


Figure 17: Impulse Responses for NIPA4_pi under identification **Error! Reference source not found.**



Note: The identified shocks in NIPA4_pi under identification **Error! Reference source not found.** are quite different from the structural residuals retrieved elsewhere in this paper. We mechanically use the same labels to denote the shocks, but it should be understood that the former are better thought of as linear combinations of the latter.

Figure 18: FEVDs for NIPA4_sp (NIPA_h without *pi*)

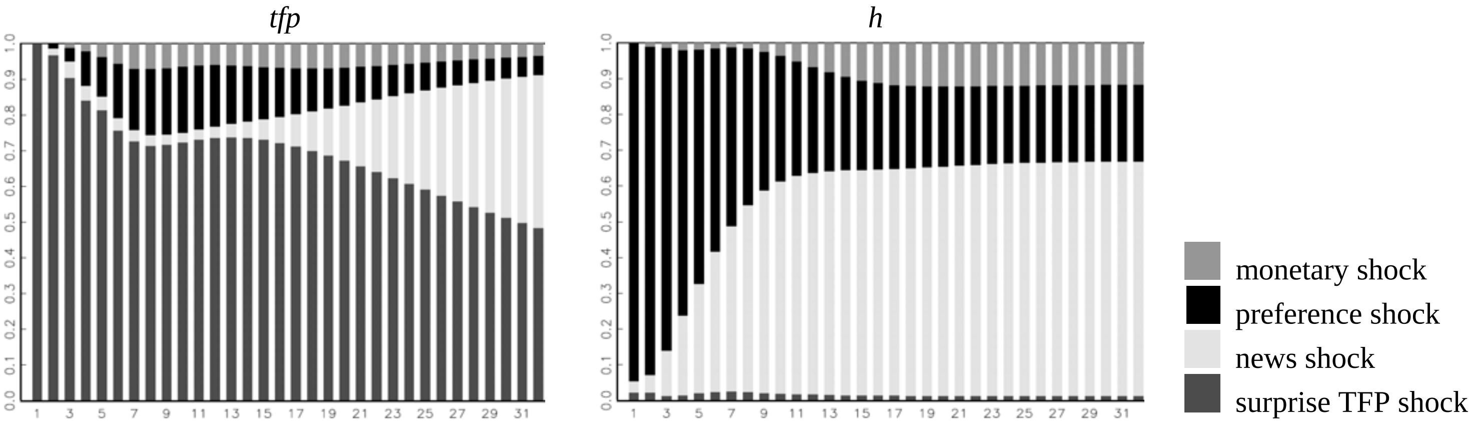


Figure 19: Impulse Responses for NIPA4_sp (NIPA_h without *pi*)

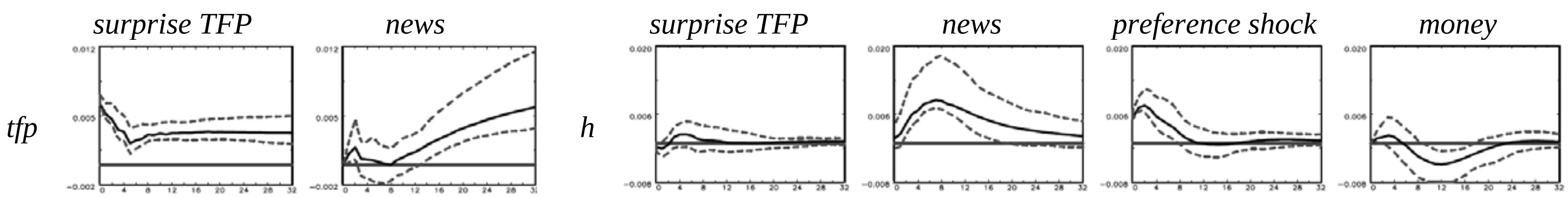


Figure 20: FEVDs for NIPA4_c (*c* replaces *sp*)

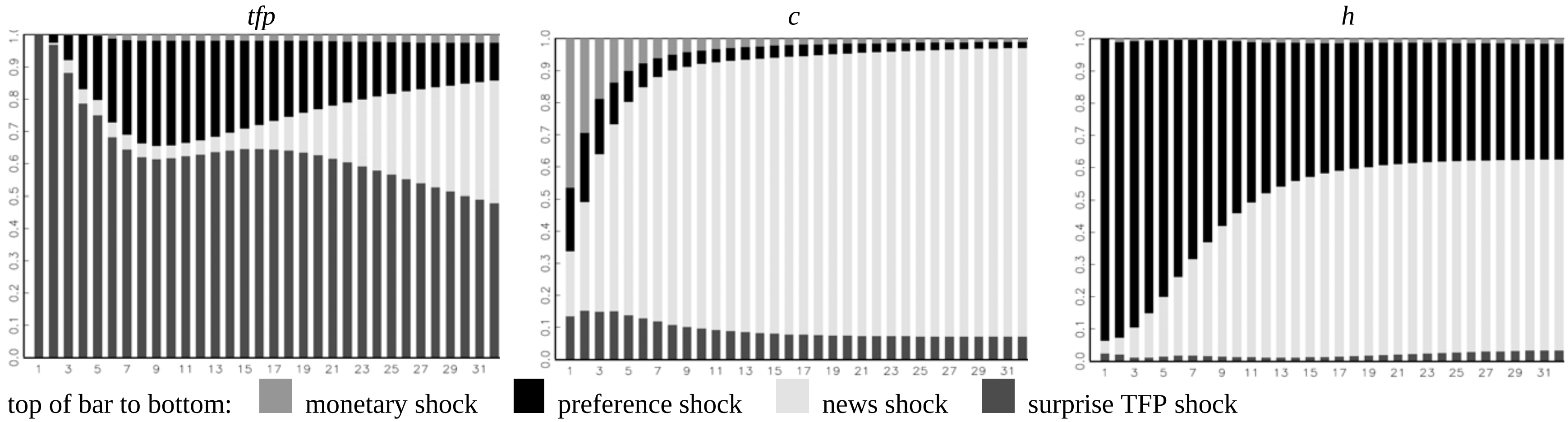


Figure 21: Impulse Responses for NIPA4_c (*c* replaces *sp*)

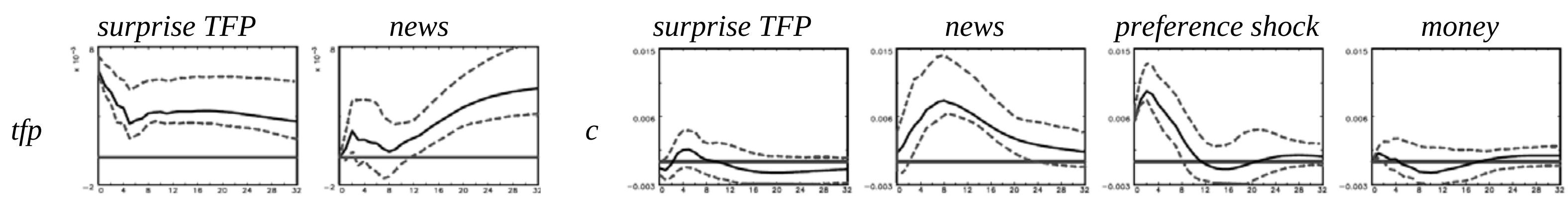


Table 4 Robustness with respect to identification						
Restrictions from A	$b_{12}=0$	$b_{21}=0$	$b_{23}=0$	$l_{12}=0$	$l_{21}=0$	$l_{23}=0$
$b_{12}=0$		n.i.	0.02 0.06 0.63	0.02 0.06 0.63	n.i.	0.02 0.02 0.66
$b_{21}=0$	n.i.		0.03 0.06 0.63	0.02 0.05 0.65	0.19 0.51 0.02	0.02 0.03 0.66
$b_{23}=0$	0.02 0.01 0.73	0.03 0.01 0.73		0.06 0.02 0.63	0.02 0.06 0.63	n.i.
$l_{12}=0$	0.02 0.11 0.63	0.01 0.10 0.66	0.02 0.01 0.73		0.03 0.06 0.63	0.01 0.04 0.66
$l_{21}=0$	n.i.	0.21 0.53 0.02	0.02 0.01 0.73	0.03 0.12 0.62		0.02 0.02 0.66
$l_{23}=0$	0.02 0.05 0.70	0.02 0.05 0.70	n.i.	0.01 0.06 0.70	0.03 0.05 0.70	

Results below (above) the diagonal are for identifications combining R_1 (R_2) and the respective row and column restrictions. Entries give the share of hours variance at eight quarters for the TFP shock, the IST shock and the news shock (in descending order). n.i.=not identified.