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Does Sentiment Matter?

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Does Sentiment Matter?*

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Abstract

We make two contributions to the literature exploring the role of sentiment in macroeconomic fluctuations:

(I) Working with the theoretical MA representations of standard DSGE models, we show that several SVAR-based approaches to the identification of sentiment shocks are unreliable, as (e.g.) they identify such disturbances even when the model does not feature them. The approach proposed by Beaudry *et al.* (2011), for example, identifies sentiment shocks within Smets and Wouters' (2007) model. The problem is that the restrictions which are typically imposed are so weak and generic that they will always be satisfied with non-negligible probability by random rotations of the model's structural disturbances, irrespective of the fact that they do, or do not include a pure sentiment shock.

(II) We derive robust restrictions for the identification of sentiment shocks based on the model of Angeletos *et al.* (2018), and working with the theoretical MA representation of the model we show that they allow to recover the shocks' IRFs and fractions of forecast error variance either exactly, or with great precision. When we impose these restrictions upon the data within a structural VAR framework, we consistently detect a minor-to-negligible role for sentiment shocks in business-cycle fluctuations.

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1 Introduction

In recent years, a vast literature has explored the idea that macroeconomic fluctuations may originate largely, or even to a dominant extent, from autonomous fluctuations in consumer sentiment.

In this paper we contribute to this literature by making two main points:

First, working with the theoretical moving average (MA) representations of several standard dynamic stochastic general equilibrium (DSGE) models, we show that existing approaches to the identification of 'sentiment shocks' are unreliable, as they identify such disturbances even when the model does not feature them. The approach used by Beaudry *et al.* (2011) and Nam and Wang (2016), for example, identifies sentiment shocks within Smets and Wouters' (2007; henceforth, SW) model, which, by construction, does not feature them. By the same token, we show that the popular approach of identifying sentiment shocks as innovations to measures of consumer confidence detects an entirely spurious role for autonomous fluctuations in sentiment even when the DSGE model is block-recursive by construction, so that consumer confidence does not Granger-cause other variables, and 'pure sentiment' shocks only affect consumer confidence. We argue that this is not by chance, and it should rather be expected, since the restrictions imposed by (e.g.) Beaudry *et al.* (2011), Nam and Wang (2016), and by Dées and Güntner (2014), are extremely weak and generic, and will therefore be satisfied with a non-negligible probability by random rotations of the model's true structural disturbances, irrespective of the fact that such disturbances do, or do not include a pure sentiment shock.

Second, working within a structural VAR (SVAR) framework, we derive robust sign restrictions—along the lines of Canova and Paustian (2011)—from the model of Angeletos *et al.* (2018; henceforth, ACD), which features pure sentiment shocks alongside more traditional drivers of macroeconomic fluctuations, such as investment-specific (IS) and neutral (N) permanent technology shocks, and (transitory) monetary policy shocks. Working with the theoretical MA representation of the ACD model, we show that these restrictions allow to exactly recover permanent IS and N shocks; and to recover with great precision all of the remaining structural disturbances (in spite of the presence of uncertainty pertaining to the random rotation matrices we use in order to impose the robust sign restrictions). We then impose the identifying restrictions on the data, working with systems featuring standard macroeconomic variables and several alternative measures of consumer confidence. An extremely robust finding, which holds for all of the systems we consider, is that the identified sentiment shocks consistently explain small-to-negligible fractions of the forecast error variance (FEV) of all variables, including all of the confidence indices themselves. A crucial point to stress is that permanent IS and N shocks already jointly explain large-to-dominant portions of the FEV of all variables at the business-cycle frequencies, i.e., the frequencies the 'sentiment' literature has consistently focused upon (see ACD, 2018). Since (i) the presence of these two disturbances is essentially unquestioned in the macroeconomic profession;[1] (*ii*) the way we identify them, *via* Uhlig's (2003, 2004) approach, is standard; and (*iii*) as mentioned, our restrictions allow to exactly recover the two shocks in population conditional on the theoretical MA representation of the ACD model, the fact that these two shocks jointly explain large-to-dominant portions of the FEV of all variables at the business-cycle frequencies puts a robust upper bound on the role pure sentiment shocks might play. To put it differently, since permanent IS and N shocks are unquestionably there, and they play a large role in driving business-cycle fluctuations, even in the implausible circumstance in which sentiment shocks explained *all* of the residual FEV of macroeconomic variables not explained by IS and N shocks, this would not amount to much. A key point to stress is that this result is independent of the fact that the other shocks are identified *via* the robust sign restrictions implied by the ACD (2018) model. Once we take into account that, beyond IS and N shocks, several other macroeconomic disturbances (e.g., monetary and fiscal policy shocks) are unquestionably there, and that, as we show, they do account in fact for some of the FEV of the data, the possibility that sentiment shocks might play a non-negligible, or even important role at driving business-cycle fluctuations appears even more remote. Our results are therefore consistent with those of Feve and Guay (2018), who working within a SVAR framework, and with identifying restrictions different from ours, conclude that sentiments shocks *'explain little of quantities and prices'*, and they *'mostly appear as an idiosyncratic component of confidence.'*

Finally, in passing we reconsider the issue of whether survey measures of either consumer or CEO confidence Granger-cause standard macroeconomic time series. We consider eleven indices and sub-indices of consumer confidence from the Michigan survey, and three from the Conference Board; and four indices of CEO confidence from the Conference Board. The null of no Granger-causality of confidence indices onto macroeconomic time series is almost uniformly rejected, most of the times very strongly. This is the case not only for small systems featuring just two additional macro variables—for which this result should logically be expected—but also, and notably, for larger systems featuring either six or twelve additional macro series. Although these results do not rule out the possibility that other approaches (i.e., dynamic factor analysis) might 'kill off' the additional informational content of confidence indices, they are however compatible with the notion that these indices do indeed contain independent information which might be pure sentiment.

The paper is organized as follows. In Section 2 we show that several existing approaches to the identification of sentiment shocks are unreliable, as (e.g.) they identify such disturbances even when the model does not feature them. In Section 3 we reconsider the issue of whether confidence indices do, or do not Granger-cause standard macroeconomic time series. In Section 4 we derive robust sign restrictions from the ACD (2018) model and, working with the theoretical MA representation of

[1]For IS shocks, see e.g. Greenwood, Hercowitz, and Huffmann (1988), Greenwood, Hercowitz, and Huffmann (1997), Greenwood, Hercowitz, and Krusell (2000), and Fisher (2006). For N shocks, see e.g. Barsky and Sims (2011).

the model, we show that these restrictions allow to recover the structural disturbances. In Section 5 we we estimate SVARs featuring standard macroeconomic variables and several alternative measures of consumer confidence, and we impose the identifying restrictions we previously derived. A consistent finding is that the identified sentiment shocks explain small-to-negligible fractions of the FEV of all variables, including the confidence indices themselves. Section 6 concludes the paper.

2 Assessing Existing Approaches to Identifying Confidence Shocks: A DSGE Perspective

2.1 Beaudry *et al.* (2011) and Nam and Wang (2016)

Working within a structural VAR framework, Beaudry *et al.* (2011) and Nam and Wang (2016) identify sentiment shocks by imposing the set of zero and sign restrictions on impact which we report in the table below.

Zero and sign restrictions from Beaudry et al. (2011) and Nam and Wang (2016)

	TFP	Stock price	Consumption	Real interest rate
Scheme I	0	+	?	?
Scheme II	0	+	+	?
Scheme III	0	+	+	+

where '0', and '+' mean that the impact has been restricted to be zero and non-negative, respectively, whereas '?' means that it has been left unrestricted. Finally, in all of the models they estimate, GDP, investment, and hours are left unrestricted. Beaudry *et al.* (2011) thus comment on the restrictions:

> 'The impulse responses of variables are restricted to be zero (0) on impact, non-negative (+) on impact, or unrestricted (blank) in either the five-variable system (with TFP, Stock Price, Consumption, Real Interest Rate, Hours), the seven-variable system (with TFP, Stock Price, Consumption, Real Interest Rate, Hours, Investment, Output), or the eight-variable systems where an additional variable of interest is added to the seven-variable system.'

Based on the *theoretical moving average* (MA) representation of Smets and Wouters' (2007) model—i.e., a model which does *not* feature pure sentiment shocks by construction—we now show that the mechanical application of these restrictions spuriously identifies sentiment shocks which turn out to explain non-negligible fractions of the forecast error variance (FEV) of macroeconomic variables. An important point to stress is that since we are here working in population, in *no way* our results hinges on issues such as small samples and the like: Rather, it simply results from the fact that the set of restrictions reported in Table 1 is so weak that it is inevitably going to be satisfied by a non-negligible fraction of (random) rotations of an initial estimate of the model's structural impact matrix. Another way of putting this is that these restrictions are so *generic* that, when a researcher randomly rotates (say) the Cholesky factor of the covariance matrix of innovations of SW's (2007) model, (s)he will obtain, with a non-negligible probability, a linear combination of the model's true structural shocks which end up satisfying these restrictions. These identified 'sentiment' shocks will therefore be nothing but linear combinations of the seven true structural shocks perturbing SW's model, which just happens to satisfy the restrictions reported in the Table.

We uniquely focus on scheme III, which imposes the largest number of restrictions, and, as a matter of logic, should therefore be regarded as the more reliable based on the arguments in (e.g.) Fry and Pagan (2011). It is to be noticed however, that Scheme I is manifestly problematic for a very simple reason: As in Beaudry and Portier (2006), a shock which leaves TFP unaffected on impact, and causes stock prices to jump, could well be a TFP news shock: In fact, this is one of the schemes used by Beaudry and Portier (2006) in order to identify such shocks. This provides an extreme example of a problem we will repeatedly discuss in this section: Existing approaches to the identification of sentiment shocks suffer from the shortcoming that they tend to incorrectly identify *other* disturbances as sentiment shocks.

We solve SW's model conditional on their modal estimates for either the 1966Q1-1979Q2 or the 1984Q1-2004Q4 periods. The *only*, entirely minor change we make to SW's model is that we replace their monetary rule—which was quite convoluted and non-standard, involving, e.g., the change in log GDP—with a standard Taylor rule with smoothing, i.e., with $R_t = \rho R_{t-1} + (1-\rho)[\phi_\pi \pi_t + \phi_y y_t]$, where R_t, π_t, and y_t are the FED Funds rate, inflation, and the output gap.[2] Other than that, the model we are working with is identical to SW's. Based on the state-space representation of the model, we then compute the structural MA representation for the following seven variables, which we collect in the vector Y_t: Neutral technology (i.e., TFP), GDP, consumption, investment, the FED Funds rate, inflation, and Tobin's Q (which is conceptually related to stock prices):

$$Y_t = A_0\epsilon_t + A_1\epsilon_{t-1} + A_2\epsilon_{t-2} + A_3\epsilon_{t-3} + A_4\epsilon_{t-4} + ... \qquad (1)$$

where the A_j's are the MA matrices in the structural MA representation of SW's model, and ϵ_t is the vector collecting the seven structural shocks (to neutral technology, investment-specific technology, ...). It is worth noticing that, in expression (1), A_0 is the true structural impact matrix of the shocks for SW's model.

We take as initial estimate of the structural impact matrix we will ultimately identify based on the restrictions reported in Table 1 the Cholesky factor of $A_0 A_0'$.

[2] The parameters ρ, ϕ_π, and ϕ_y are set at Smets and Wouters' (2007) modal estimates.

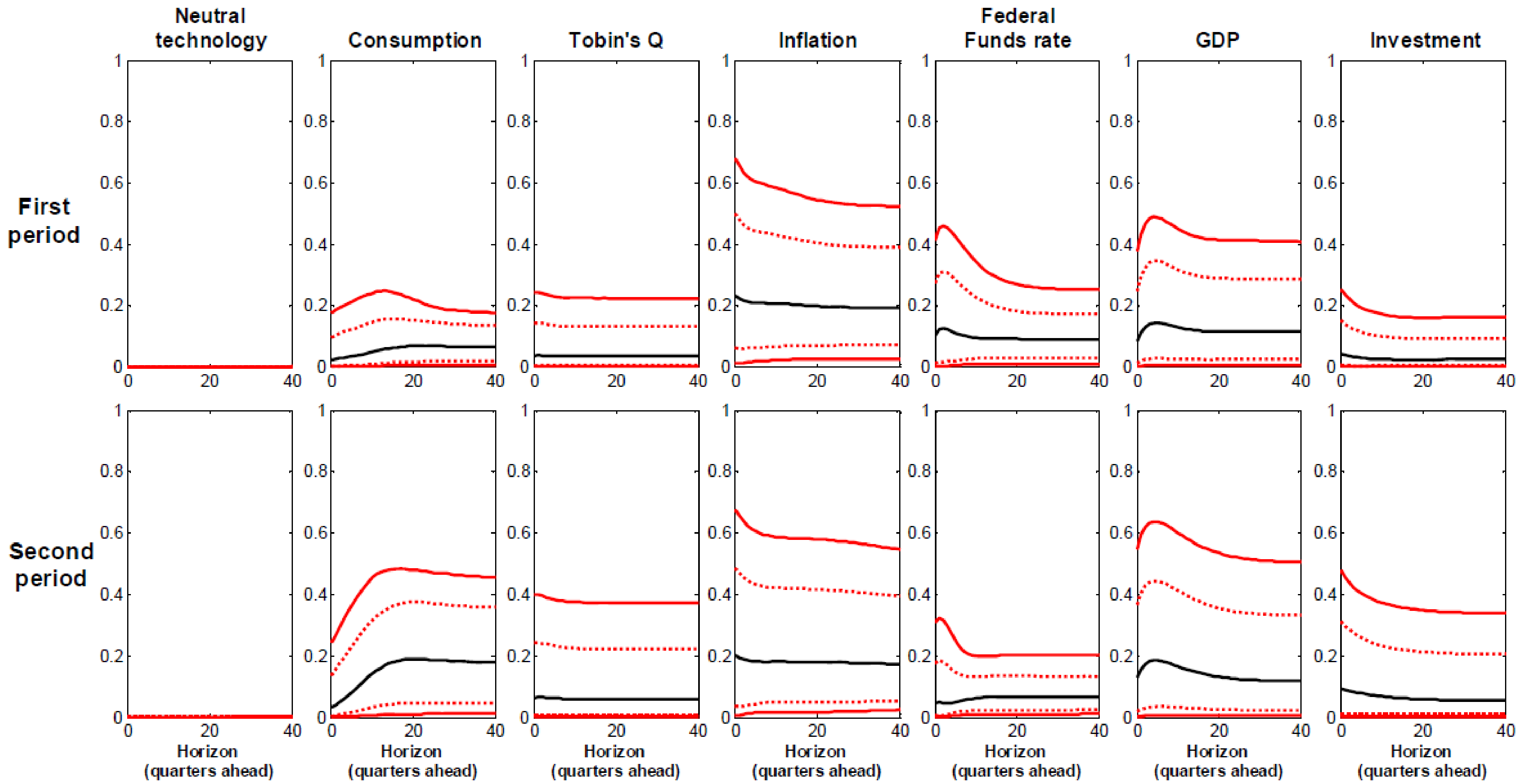

Figure 1 Spuriously identifying confidence shocks in Smets and Wouters' (2007) model *via* Beaudry *et al.*'s (2011) identification strategy: Fractions of forecast error variance explained by the 'identified' confidence shock

Let this starting estimate be A_0^*. Then, we rotate A_0^* *via* the algorithm for combining zero and sign restrictions proposed by **?**. For j = 1, 2, 3, ..., N, with N = 100,000, we consider a single random rotation matrix implementing the zero restrictions on A_0^j (with A_0^j being the candidate structural impact matrix), which we generate *via* Arias *et al.*'s (2014) Algorithm 5.[3] Then, if the sign restrictions are all satisfied, we keep A_0^j. Otherwise, we discard it. In this way, we build up the statistical distribution of the A_0^j's conditional on (i) SW's model's covariance matrix of innovations, and (ii) the zero and sign restrictions reported in Table 1. Finally, for each of the A_0^j's we compute the fraction of FEV of the seven variables at horizons up to 40 quarters which is explained by the identified sentiment shock.

Figure 1 reports the median, together with the 16-84, and the 5-95 percentiles of the distributions of the fractions of FEV of either variable explained by the identified sentiment shock. Based on the medians of the distributions, the fractions of explained FEV are uniformly quite low, and in the case of TFP they are exactly zero at all horizons, reflecting the fact that (i) in the VAR representation of SW's model, TFP only depends on itself lagged, and (ii) the identified sentiment shocks, by assumption, do not impact on TFP at t=0.

The key point here, however, is that these results are entirely spurious, and they are simply the figment of imposing upon the data generating process (DGP) a set of very weak restrictions. Furthermore, if we focus on the 5-95 credible sets, for several variables these shocks explain non-negligible fractions of FEV. This is the case, in particular, for inflation, GDP, and consumption in the second period.

2.2 Identifying shocks to measures of consumer sentiment

One popular approach to identifying sentiment shocks is based on the notion of identifying innovations to measures of consumer confidence (see, e.g., Dées and Güntner (2014)). As we now show by example, this approach is also unreliable for the simple reason that it mechanically identifies sentiment shocks even within environments in which consumer sentiment is, by construction, a pure linear measure of macroeconomic variables.

The easiest way to illustrate this is *via* the standard three-equations backward- and forward-looking New Keynesian model:

$$R_t = \rho R_{t-1} + (1-\rho)[\phi_\pi \pi_t + \phi_y y_t] + \epsilon_{R,t} \tag{2}$$

$$\pi_t = \frac{\beta}{1+\alpha\beta}\pi_{t+1|t} + \frac{\alpha}{1+\alpha\beta}\pi_{t-1} + \kappa y_t + u_t \tag{3}$$

$$y_t = \gamma y_{t+1|t} + (1-\gamma)y_{t-1} - \sigma^{-1}[R_t - \pi_{t+1|t}] + v_t \tag{4}$$

[3] See Arias *et al.* (2014) p. 18 (the version of the paper we are referring to is dated September 7, 2014). Notice that although Arias *et al.*'s paper discusses a more general algorithm based on Gibbs-sampling, as they point out *'[...] when the researcher is interested in identifying only one shock, the Gibbs sample step in Algorithm 4 is not necessary, and one should obtain q from Algorithm 5.'*

where the notation is obvious; R_t, π_t and y_t are the nominal interest rate, inflation, and the output gap, respectively; and $\epsilon_{R,t}$, u_t, and v_t are three white noise structural disturbances, $\epsilon_{R,t} \sim N(0, \sigma_R^2)$, $u_t \sim N(0, \sigma_u^2)$, $v_t \sim N(0, \sigma_v^2)$.

We calibrate this model based on Benati's (2008, Table 12) modal Bayesian estimates for the United States for the full sample, and for the period after the Volcker stabilization, respectively. Conditional on these parameters' values, the model (2)-(4) has a structural VAR(2) representation. It is to be noticed that, in this model, output is equal to consumption, i.e. $y_t = c_t$. We then artificially create a measure of consumer confidence, Ξ_t, such that $\Xi_t = c_t + \eta_t$, $\eta_t \sim N(0, \sigma_\eta^2)$, where η_t is an authentic, exogenous innovation to consumer confidence which we make as small as possible, under the only constraint that the resulting VAR representation for $Y_t \equiv [R_t, \pi_t, y_t, \Xi_t]'$ is not stochastically singular. Specifically, we set $\sigma_\eta^2 = 10^{-12}$, which implies that the fractions of forecast error variance of R_t, π_t, and y_t explained by η_t are, for all practical purposes, *nil*.

The resulting structural VAR(2) representation for Y_t for the full sample period is then given by

$$\begin{bmatrix} R_t \\ \pi_t \\ c_t \\ \Xi_t \end{bmatrix} \equiv Y_t =$$

$$= \underbrace{\begin{bmatrix} 1.1490 & 0.2562 & 0.5352 & 0 \\ -0.0258 & 0.8269 & 0.0920 & 0 \\ 0.0401 & 0.2089 & 1.2940 & 0 \\ 0.0401 & 0.2089 & 1.2940 & 0 \end{bmatrix}}_{B_1} Y_{t-1} + \underbrace{\begin{bmatrix} -0.2362 & -0.1569 & -0.3476 & 0 \\ -0.0016 & -0.0022 & -0.0350 & 0 \\ -0.0711 & -0.1705 & -0.3521 & 0 \\ -0.0711 & -0.1705 & -0.3521 & 0 \end{bmatrix}}_{B_2} Y_{t-2} +$$

$$+ \underbrace{\begin{bmatrix} 0.5789 & -0.1029 & -0.3515 & 0 \\ -0.0156 & -0.7151 & 0.4581 & 0 \\ -0.3053 & 0.3859 & 0.3555 & 0 \\ -0.3053 & 0.3859 & 0.3555 & 10^{-6} \end{bmatrix}}_{A_0} \epsilon_t, \qquad (5)$$

Notice how (*i*) up to η_t, the fourth row of (5) is identical to the third, thus reflecting the fact that that $\Xi_t = c_t + \eta_t$, and (*ii*) Ξ_t is Granger-caused by all of the other variables in the system, but it does not Granger-cause any of them. In plain English, this means that within (5) the role played by authentic, exogenous shocks to consumer confidence is virtually *nil*.

We now apply to (5) the methodology of (e.g.) Dées and Güntner (2014), identifying sentiment shocks based on the restriction that, in response to a positive 'wave of optimism', consumer confidence, consumption, and the real interest rate do not decrease. As in Section 3.1, we work in population, that is, based on the theoretical structural VAR representation (5). Specifically, taking the matrix A_0 in (5) as the

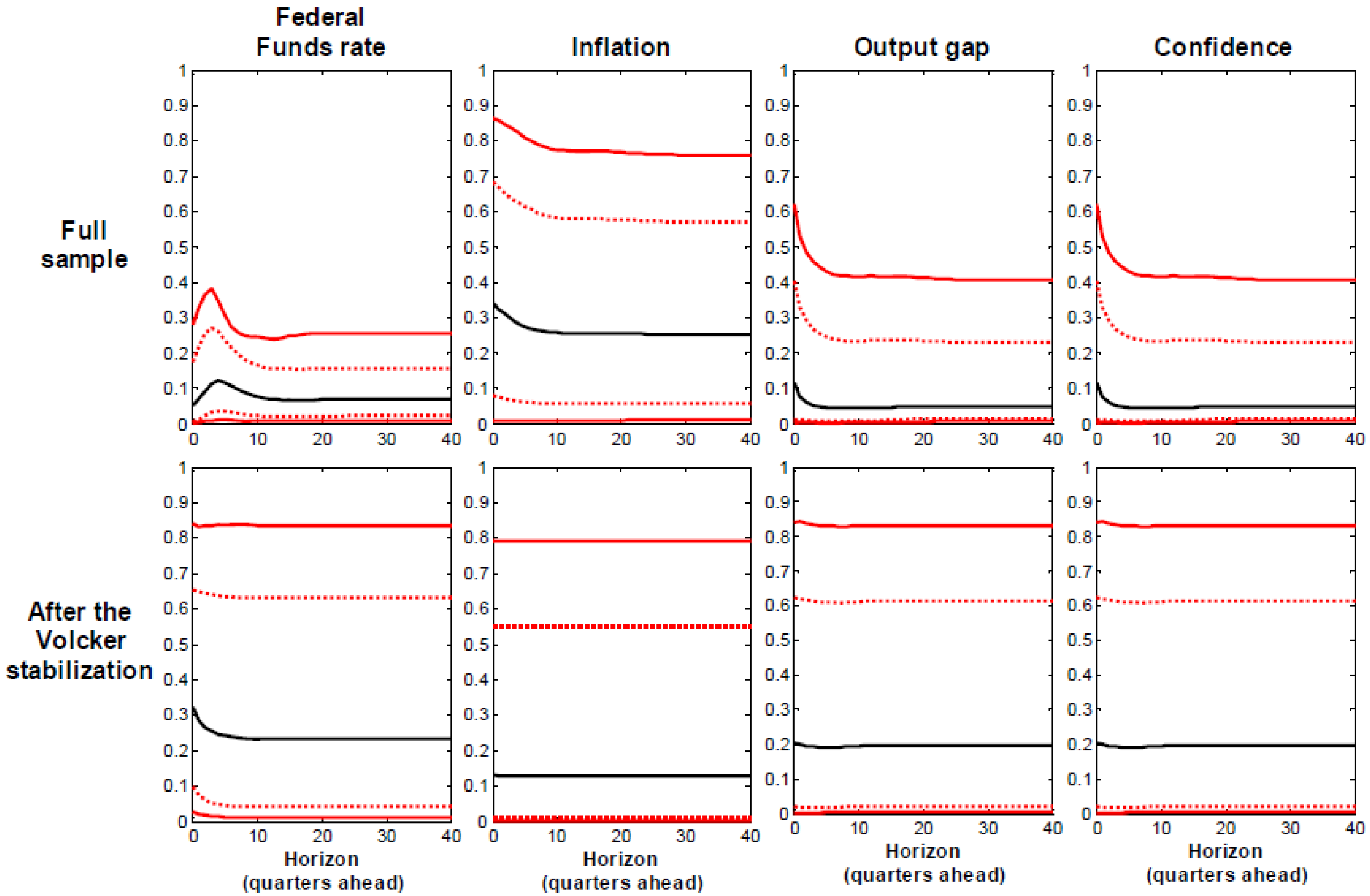

Figure 2 Spuriously identifying confidence shocks in the standard New Keynesian model *via* sign restrictions: Fractions of forecast error variance explained by the 'identified' confidence shock

starting estimate of the structural impact matrix we want to identify *via* sign restrictions, we generate $N = 100{,}000$ random rotation matrices *via* the algorithm proposed by Dées and Güntner (2014). For each random rotation matrix Q_j, $j = 1, 2, ..., N$ we the compute the corresponding candidate impact matrix $A^*_{0,j} = A_0 Q_j$. Finally we keep, among all of the $A^*_{0,j}$'s, only those satisfying the previously mentioned sign restrictions, thus obtaining their distribution.

Figure 2 shows the results. Although the median estimates are uniformly quite low, once again, it ought to be stressed that these results are entirely spurious, since for all series the true values are uniformly *nil*. Further, (i) if we focus instead on the 5-95 credible sets, the results are uniformly bad, with (e.g.) the upper bound for inflation being around 80 per cent for either period; and (ii) in a few cases—inflation for the full sample, and the other series for the period after the Volcker stabilization—even the median fractions of FEV are definitely non-negligible.

2.3 Why do these approaches fail?

Why do the approaches discussed in the previous sub-sections fail to correctly identify the (non-existent) role of pure sentiment shocks within the underlying DGPs? The reason is straightforward, and it boils down to the fact that the restrictions imposed by Beaudry *et al.* (2011) and Nam and Wang (2016), and by Dées and Güntner (2014), are so *weak* and *generic* that they will necessarily be satisfied with a non-negligible probability by random rotations of the model's true structural disturbances, irrespective of the fact that such disturbances do, or do not include a pure sentiment shock.

Conceptually in line with Canova and Paustian (2011)—and more generally with Fry and Pagan's (2011) critique of sign restrictions as being 'weak information'—in what follows we will therefore impose upon the VARs we work with a significantly more informative set of restrictions, which will allow us to obtain sharper inference. All of the restrictions will be derived based on the model of ACD (2018). To anticipate, those pertaining to permanent IS and N shocks are standard in the literature (e.g., IS shocks are assumed to be the only driver of the unit root component of the relative price of investment), whereas those pertaining to the other (transitory) disturbances will be derived as 'robust sign restrictions' as in Canova and Paustian (2011).

Before doing that, however, we reconsider the issue of whether survey measures of consumer and business confidence do, or do not Granger-cause macro variables. A key reason for doing this is that if, in fact, these measures did Granger-cause macro variables, this would suggest that such indices contain information about sentiment which is not contained in other macro series, thus strengthening the case for including them in the VARs.

3 Do Survey Measures of Confidence Granger-Cause Macro Variables?

In this section we perform Granger causality tests of either consumer or CEO (i.e., business) confidence indices onto macroeconomic variables. As we will see, the null of no Granger-causality of survey measures onto macro variables is strongly and near-uniformly rejected across the board, even for systems featuring either six or twelve additional variables. Although this is by no means a hard proof that such additional information is pure sentiment, it is at the very least compatible with such a notion.

3.1 Testing for no Granger-causality

Tables 1 and 2 report Wald tests for the null hypothesis of no Granger-causality of confidence indices onto macroeconomic variables, together with bootstrapped p-values. The p-values (which are based on 10,000 bootstrap replications for each model) have been computed by bootstrapping the VAR model estimated under the null, that is, by imposing that confidence indices do *not* Granger-cause the other variables in the VAR. The model estimated under the null has then been bootstrapped, and based on each bootstrapped replication we have performed the same Wald test for no-Granger causality we had previously performed based on the actual data, thus building up the empirical distribution of the test statistic under the null.

For either confidence index—either from the University of Michigan, or from the Conference Board; and either pertaining to consumers, or to CEOs—we consider two sample periods: The former sample excludes the Zero Lower Bound (ZLB) period, which means that we end it in 2008Q3, the last quarter for which we can reasonably be sure that the ZLB was not binding; the latter sample also includes the period since 2008Q3.

For either period, and either confidence index we consider three different models, featuring 3, 7, and 13 variables respectively. The smallest model includes, beyond the confidence index, the log-difference of real GDP *per capita*, and the logarithm of the consumption/GDP ratio. The intermediate model also includes GDP deflator inflation, the logarithm of hours worked *per capita*, the log-difference of the relative price of investment, and the *ex post* real FED Funds rate. Finally, the largest model further includes the logarithm of the investment/GDP ratio, the BAA-AAA spread, the spread between the 1-year government bond yield and the FED Funds rate; and the spread between the 3-year and the 1-year, the 5-year and the 3-year, and the 10-year and the 5-year government bond yields. All of the series included in the VARs are I(0) according to the results of Elliot, Rothenberg, and Stock (1996) unit root tests (these results are not reported here for reasons of space, but they are available upon request).

Evidence from the two tables rejects almost uniformly, and typically very strongly, the null hypothesis of no Granger-causality of confidence indices for the other variables

Table 1 Wald tests for Granger-causality of consumer confidence indices from the Michigan survey onto macroeconomic variables, and bootstrapped p-values[a]

	Excluding the ZLB			*Full samples*		
	N=3	N=7	N=13	N=3	N=7	N=13
Consumer Confidence Index						
Index 1: Overall Index	2.28 (0.00)	3.73 (0.01)	5.36 (0.10)	2.50 (0.00)	3.65 (0.00)	5.88 (0.01)
Index 2: Current Index	1.91 (0.00)	3.45 (0.01)	5.15 (0.14)	2.22 (0.00)	4.00 (0.00)	6.97 (0.00)
Index 3: Expected Index	2.12 (0.00)	3.74 (0.01)	5.89 (0.04)	2.15 (0.00)	3.18 (0.01)	5.43 (0.03)
Index Components						
Index 4: Personal Finances: Expected	1.62 (0.01)	2.99 (0.05)	4.49 (0.31)	1.40 (0.01)	2.57 (0.07)	5.08 (0.05)
Index 5: Business Conditions: 12 Months Ahead	2.20 (0.00)	3.98 (0.00)	5.90 (0.04)	2.33 (0.00)	3.52 (0.00)	5.48 (0.03)
Index 6: Business Conditions: 5 Years Ahead	1.86 (0.00)	3.52 (0.01)	6.00 (0.04)	1.78 (0.00)	2.81 (0.04)	4.81 (0.10)
Answers to Questions[b]						
Index 7: Question 1	1.62 (0.01)	3.03 (0.04)	4.56 (0.28)	1.45 (0.01)	2.67 (0.06)	5.25 (0.040)
Index 8: Question 2	1.24 (0.05)	2.24 (0.33)	5.36 (0.18)	1.44 (0.01)	2.15 (0.26)	5.48 (0.05)
Index 9: Question 3	2.38 (0.01)	3.86 (0.01)	6.59 (0.03)	2.06 (0.00)	3.53 (0.01)	5.33 (0.07)
Index 10: Question 4	2.20 (0.00)	3.98 (0.00)	5.90 (0.04)	2.33 (0.00)	3.52 (0.00)	5.48 (0.03)
Index 11: Question 5	1.86 (0.00)	3.52 (0.01)	6.00 (0.03)	1.78 (0.00)	2.81 (0.04)	4.82 (0.10)

[a] Based on 10,000 bootstrap replications. [b] See respective Questions for each Index in Appendix A.

Table 2 Wald tests for Granger-causality of confidence indices from the Conference Board onto macroeconomic variables, and bootstrapped p-values[a]

	Excluding the ZLB			*Full samples*		
	N=3	N=7	N=13	N=3	N=7	N=13
Consumer Confidence Index						
Index 1: Overall Index	1.79 (0.03)	5.38 (0.01)	8.92 (0.05)	1.74 (0.02)	6.05 (0.00)	8.40 (0.01)
Index 2: Present Situation	2.39 (0.00)	6.79 (0.00)	8.72 (0.07)	1.72 (0.02)	5.91 (0.00)	
Index 3: Expectations	1.60 (0.04)	7.60 (0.04)	8.14 (0.09)	1.76 (0.01)	4.66 (0.00)	8.79 (0.00)
Measure of CEO Confidence^{TM}						
Index 4: Overall index	1.90 (0.02)	4.99 (0.01)	7.44 (0.11)	1.91 (0.01)	4.40 (0.00)	7.061 (0.03)
Index 5: Current Economic Conditions vs. 6 Months Ago	1.89 (0.01)	4.00 (0.03)	4.65 (0.78)	2.04 (0.00)	3.41 (0.03)	5.92 (0.12)
Index 6: Expectations for Economy, 6 Months Ahead	1.51 (0.05)	5.40 (0.00)	8.76 (0.03)	1.32 (0.05)	4.95 (0.00)	7.92 (0.01)
Index 7: Expectations for Own Industry 6 Months Ahead	1.85 (0.02)	5.60 (0.00)	11.31 (0.00)	1.97 (0.01)	5.23 (0.00)	7.41 (0.02)

[a] Based on 10,000 bootstrap replications.

included in the VARs. Notably, this is the case not only for systems featuring either 3 or 7 variables—for which a possible explanation could be that confidence indices do not contain any idiosyncratic information, but are just 'proxying' for macro variables which have been left out from the VAR—but also for the largest systems. To be sure, it could well be the case that if we had worked with (e.g.) FAVARs including factors extracted from large panels of macro series, the null of no Granger-causality might not have been rejected. As they stand, however, the results in Tables 1 and 2 are *at the very least compatible* with the notion that confidence indices do indeed contain idiosyncratic information, which might well be pure sentiment. This motivates our choice, in the rest of the paper, to include some confidence indices in the VARs, and to impose the restriction that pure sentiment shocks do not leave consumer or CEO confidence indices unchanged on impact (i.e., within the quarter).

4 Methodology

In what follows we will work with the VAR(p) model

$$Y_t = B_0 + B_1 Y_{t-1} + ... + B_p Y_{t-p} + u_t, \qquad E[u_t u_t'] = \Omega \tag{6}$$

where Y_t features (in this order) the logarithm of the relative price of investment (RPI); the logarithm of real chain-weighted consumption of non-durables and services, GDP, and hours worked *per capita*; GDP deflator inflation; the Federal Funds rate; and either a consumer or a CEO confidence index (from either the University of Michigan, or the Conference Board).

The specific sample periods (which are discussed in the data appendix A) depend on the starting date of individual confidence indices. For all VARs we end the sample in 2008Q3, which is the last quarter for which we can reasonably assume that the Zero Lower Bound (ZLB) on the FED Funds rate was not binding.]

4.1 Estimation

The VAR is estimated *via* Bayesian methods as in Uhlig (1998, 2005). Specifically, Uhlig's approach is followed exactly in terms of both distributional assumptions—the distributions for the VAR's coefficients and its covariance matrix are postulated to belong to the Normal-Wishart family—and of priors. For estimation details the reader is therefore referred to either the Appendix of Uhlig (1998), or to Appendix B of Uhlig (2005). Results are based on 1,000,000 draws from the posterior distribution of the VAR's reduced-form coefficients and the covariance matrix of its reduced-form innovations (the draws are computed exactly as in Uhlig (1998, 2005)). The reason for using so many draws for the reduced-form VAR is that, for each draw, we consider one—and only one—random rotation matrix computed (see sub-section 4.?) by combining the methodology of Uhlig (2003, 2004) in order to identify permanent

IS and N shocks, and the methodology of Arias *et al.* (2018) in order to identify the remaning shocks. We set the lag order to p=4. Finally, in drawing the VAR's coefficients we do not impose stationarity.

4.2 Identification

All of our identifying restrictions have been derived based on the model of ACD (2018).[4] In fact, however, the restrictions pertaining to IS and N shocks are of more general validity and, as discussed (e.g.) by Fisher (2006), they hold within any meaningful DSGE model. Specifically,

(I) IS shocks are postulated to be the only driver of the permanent component of the RPI.[5] Since within the present context we are estimating the VARs in levels, we identify IS shocks as in Uhlig (2003, 2004), as the disturbances explaining the maximum fraction of the FEV of the RPI at a 'long' horizon, which we set to 25 years ahead.

(II) Conditional on having identified IS shocks, we identify N disturbances based on the restriction that, among the remaining shocks, they explain the maximum fraction of the FEV of consumption at the same long horizon. Once again, the restriction holds exactly both within the ACD (2018) model, and more generally within any meaningful DSGE model.

(III) Conditional on having identified IS and N shocks, we then identify the remaining five shocks (discussed below) in the following way. When we work *in population* based on the theoretical MA representation of ACD's (2018) model, we impose a combination of zero and robust sign restrictions on impact based on the Gibbs-sampling algorithm proposed by Arias *et al.* (2018). The reason for imposing the zero restrictions is that, within ACD's (2018) model, IS shocks are the only driver of the RPI at all horizons, which implies that the impact at t=0 of all other shocks has to be set equal to zero. When we work with *actual data*, on the other hand, we do not impose such zero restrictions on impact, and we rather leave the impacts on the RPI at t=0 of all shocks other than IS unconstrained. The reason for doing so is that IS shocks being the only driver of the RPI at all horizons is a peculiarity of the ACD (2018) model, whereas, in general, within standard DSGE models the RPI is impacted upon, at t=0, by all structural shocks.[6] As a result, imposing upon the data the restriction that IS shocks are the only disturbances to impact upon the RPI at t=0 would likely distort the inference.

[4] ACD's (2018) model features more observed variables, and more structural shocks than the seven we consider here. The only motivation for uniquely focusing on seven variables and shocks is in order to avoid working with excessively large systems.

[5] Within the ACD (2018) model, IS shocks are the only disturbances impacting upon the RPI, which means that they are, in fact, the only driver of the RPI at all horizons.

[6] [Here put some references, e.g. the work of Justiniano, Primiceri, and Tambalotti]

4.3 Deriving the robust sign restrictions

Beyond the permanent IS and N shocks, we consider the following five transitory disturbances: a 'pure sentiment' shock, a monetary policy shock, and transitory N, government spending, and preference shocks. Conceptually in line with Canova and Paustian (2011), we derive as follows the robust sign restrictions we will impose in order to identify the shocks, where 'robust' means 'holding for an overwhelmingly large fraction of plausible random combinations of the model's parameters'.

We consider the following sets of plausible values for most of the model's structural parameters: [**Lucas: Here please put details**]. Following Canova and Paustian (2011), we then take ? draws for the parameters from Uniform distributions defined over these intervals. For each draw of the parameters, we solve the model and compute IRFs to the structural shocks, and the fractions of the FEV of the variables they explaine. The results are reported in the next table.

Table 1 Robust sign restrictions on impact based on the ACD (2018) model

	Shock:[a]				
Variable:	ϵ_t^S	ϵ_t^M	ϵ_t^G	$\epsilon_t^{N,T}$	ϵ_t^P
Consumption	+	−	−	+	+
GDP	+	−	+	+	+
RPI	0	0	0	0	0
Hours	+	−	+	−	+
Inflation	−	−	+	−	+
Interest rate	−	−	+	−	+
Expectation of individual output	+	−	+	+	+

[a] Permanent IS and N shocks are identified *via* Uhlig's (2003, 2004) approach. ϵ_t^S = sentiment shock; ϵ_t^M = monetary shock; ϵ_t^G = government spending shock; $\epsilon_t^{N,T}$ = transitory N shock; ϵ_t^P = preference shock.

In what follows we will impose the robust sign restrictions only on impact. The main reason for doing so is that, as we will show in the next sub-sections, this is already sufficient to recover all of the shocks' IRFs and fractions of FEV with great precision. Intuitively, this has to do with the fact that since we will be imposing *all* of the restrictions reported in the table,[7] we are already imposing a significant amount of information. This implies that although imposing additional restrictions at longer horizons would produce mpore precise results, in practice the gains would be limited.

Working in population—that is, based on the theoretical MA representation of ACD's model—we then turn to the issue of whether our restrictions allow to recover the shocks' IRFs and fractions of FEV.

[7] With the exception of the zero restrictions on the RPI at t=0 for shocks other than permanent IS shocks when we work with the actual data.

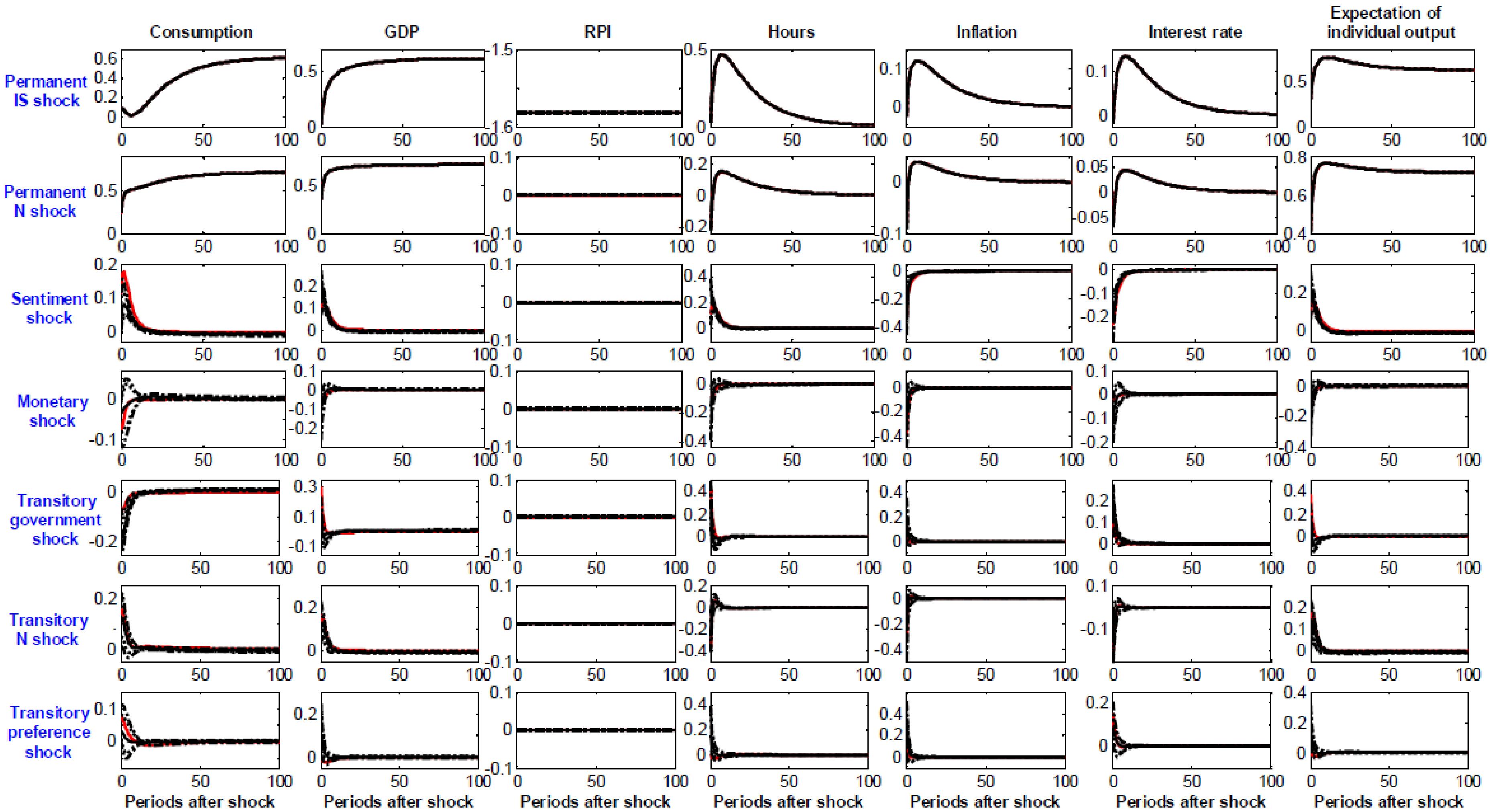

Figure 3 Recovering the IRFs of the ACD model in population (red: true IRFs; black: median, and 16-84, and 5-95 percentiles of the distribution of estimated IRFs)

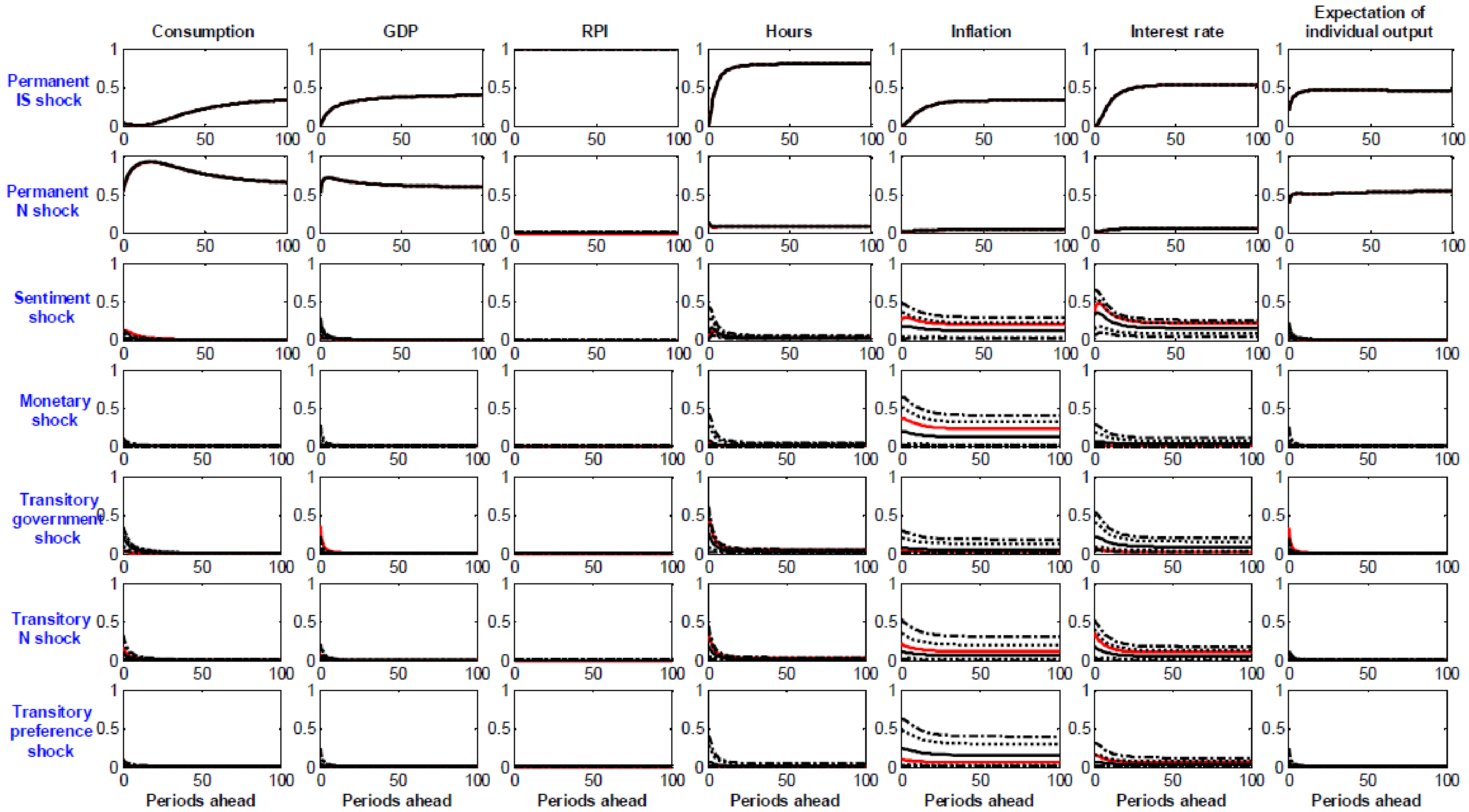

Figure 4 Recovering the fractions of FEV of the ACD model in population (red: true fractions of FEV; black: median, and 16-84, and 5-95 percentiles of the distribution of estimated fractions of FEV)

4.4 Can our restrictions recover the shocks' IRFs and fractions of FEV?

We extract from the ACD (2018) model the structural MA representation for the seven observed variables corresponding to the seven series we consider in our empirical implementation (the RPI, GDP, consumption, hours, inflation, the monetary policy rate, and the 'expectation of individual output', which, within ACD's model, plays the role of a measure of sentiment) as a function of the seven structural disturbances. The structural MA representation of the model can be trivially computed based on the model's IRFs to the seven structural shocks.

Let the theoretical structural MA representation of the model's observables be

$$Y_t = A_0\epsilon_t + A_1\epsilon_{t-1} + A_2\epsilon_{t-2} + A_3\epsilon_{t-3} + ... \tag{7}$$

where the vectors of the observables and of the structural disturbances have been defined before, and $E[\epsilon_t\epsilon_t']=I_N$, with I_N being the $(N \times N)$ identity matrix, so that each of the i-th columns (with i = 1, 2, ..., N) of the MA matrices A_0, A_1, A_2, A_3, ... has been divided by the standard deviation of the i-th shock.

Observationally equivalent reduced-form representations of (7) can be obtained by post-multiplying all of the MA matrices A_0, A_1, A_2, A_3, ... by an orthogonal rotation matrix R, yielding

$$Y_t = \tilde{A}_0\tilde{\epsilon}_t + \tilde{A}_1\tilde{\epsilon}_{t-1} + \tilde{A}_2\tilde{\epsilon}_{t-2} + \tilde{A}_3\tilde{\epsilon}_{t-3} + ... \tag{8}$$

where $\tilde{A}_j = A_jR$ and $\tilde{\epsilon}_{t-j} = R'\epsilon_{t-j}$, j = 0, 1, 2, 3, ... We can randomly generate different rotation matrices[8], thus producing different observationally equivalent VMAs. The question we wish to address is whether imposing the previously discussed identifying restrictions on different reduced form VMAs allow us to recover the true IRFs and fractions of FEV.

We have performed this exercise 100 times, and for all of these, imposing our identifying restrictions allows indeed to recover the true IRFs and fractions of FEV. Figures 3 and 4 report the results for one typical run, for the IRFs and the fractions of FEV, respectively. In both figures, the objects (either IRFs, or fractions of FEV) pertaining to IS and N shocks are exactly recovered, reflecting the fact that, for either shock, Uhlig's (2003, 2004) approach produces a single matrix for each individual reduced form VMA representation. As for the other five shocks, on the other hand, the presence of rotation uncertainty originating from the algorithm of Arias *et al.* (2018), which we use to jointly impose the zero and sign restrcitions, implies that we will have distributions for the IRFs and fractions of FEV, rather than point estimates. In most cases, however, the distributions (as captured by the reported percentiles) are quite tight, and the 16-84 percentiles contain the true IRFs and fractions of FEV at all horizons, and in all cases the 5-95 percentiles contain the true objects.

[8] We generate the $(N \times N)$ random rotation matrix as follows. We start by taking an $(N \times N)$ draw K from an N(0, 1) distribution. Then, we take the QR decomposition of K, and we set the rotation matrix to $Q\prime$.

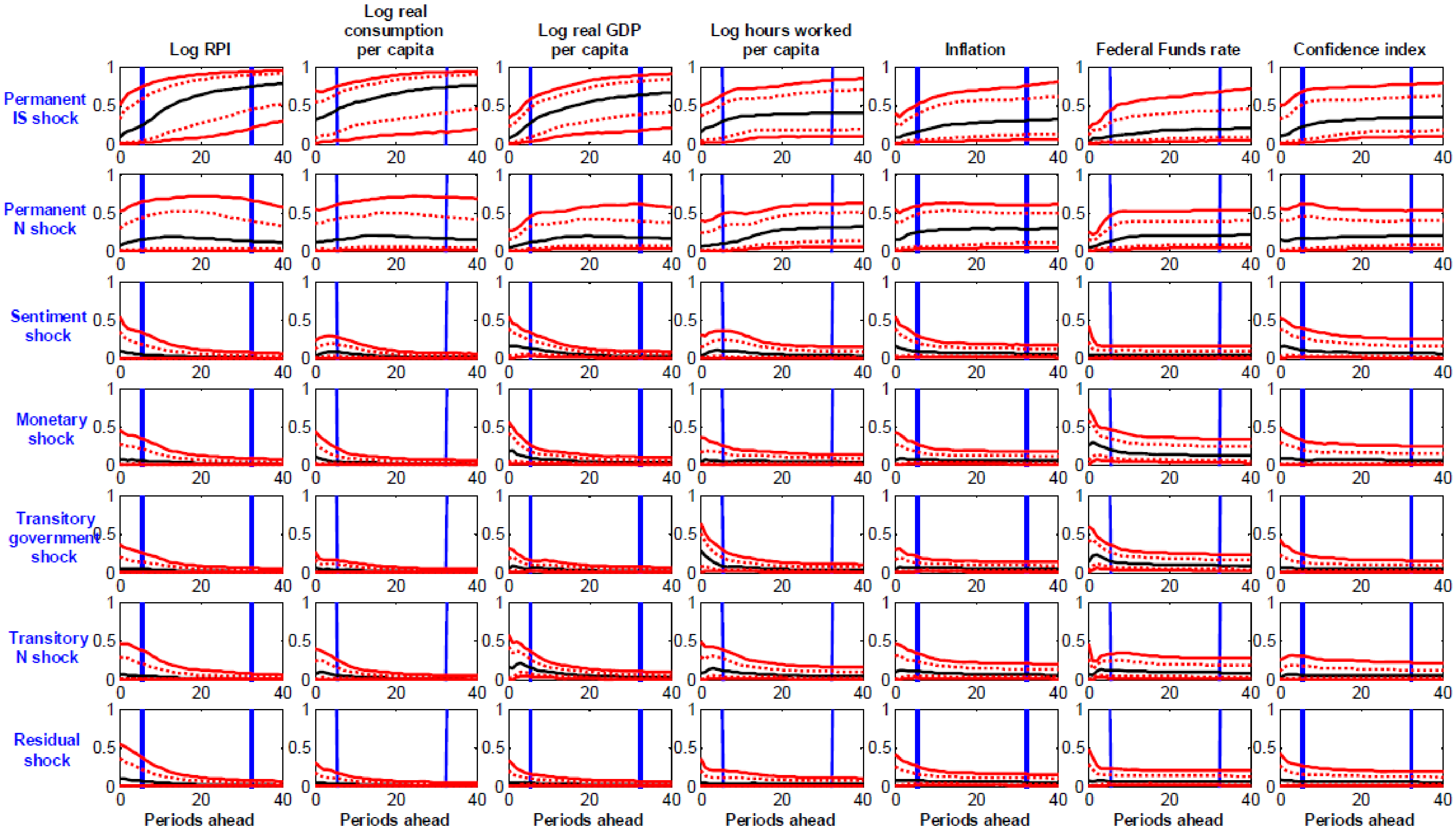

Figure 5 Estimated fractions of FEV based on the system including the Conference Board overall index (median, and 16-84, and 5-95 percentiles of the posterior distribution)

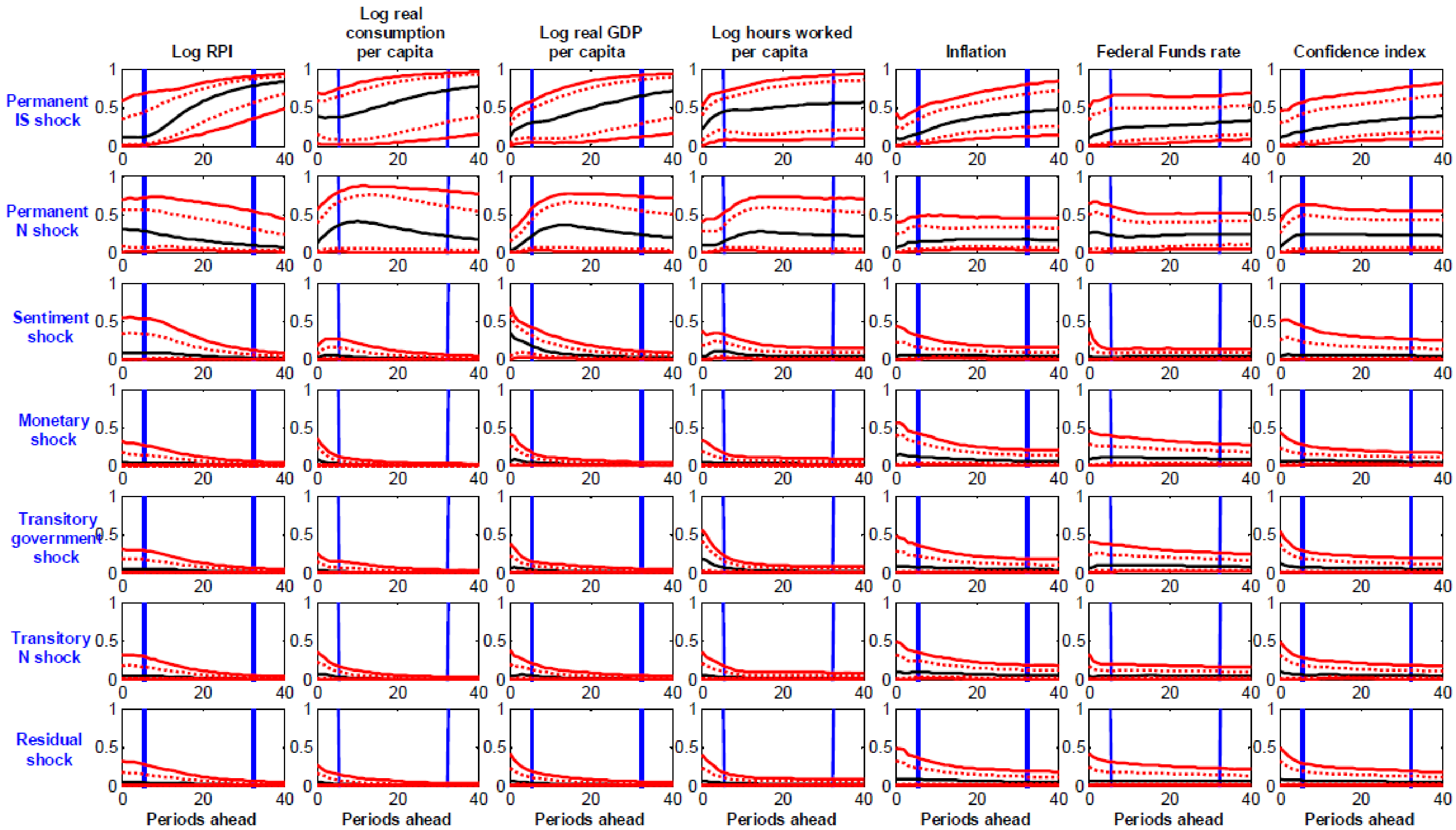

Figure 6 Estimated fractions of FEV based on the system including the University of Michigan's index 10 (median, and 16-84, and 5-95 percentiles of the posterior distribution)

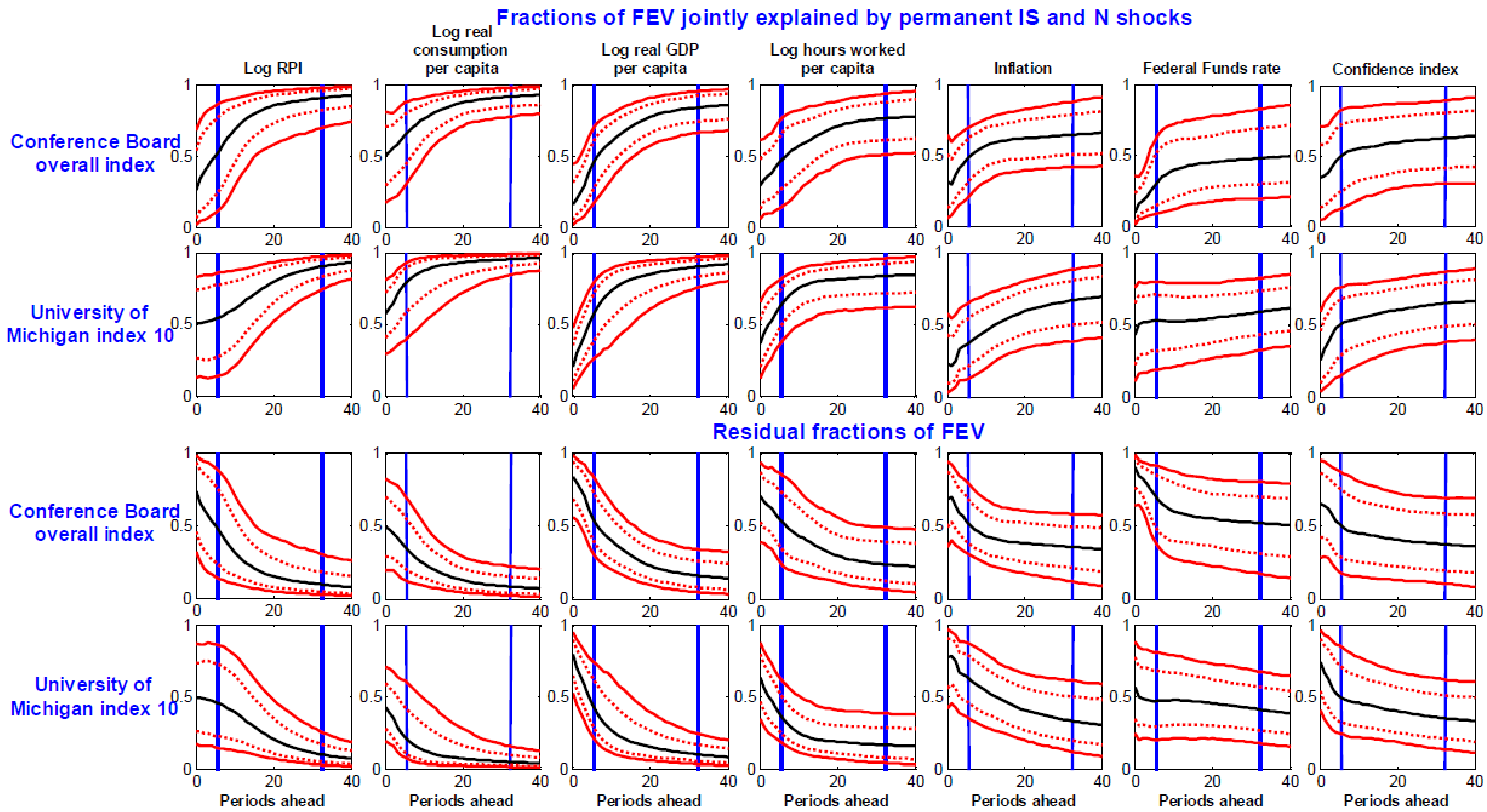

Figure 7 Estimated fractions of FEV jointly explained by permanent IS and N shocks, and residual fractions of FEV (median, and 16-84, and 5-95 percentiles of the posterior distribution)

5 Evidence

Having been reassured that our identifying restrictions allow to recover—either exactly, for permanent IS and N shocks, or with great precision, for all other disturbances—the shocks' true IRFs and fractions of FEV, we now turn to the actual data. As mentioned, the *only* difference between the restrictions we just imposed upon the theoretical reduced-form MA representation of ACD's (2018) model, and those we will impose upon the actual data, pertains to the impacts on the RPI at t=0 of all shocks other than permanent IS and N disturbances: Whereas working with the theoretical MA representation of ACD's (2018) model these impacts were restricted to zero, when we work with the actual data we will leave them unrestricted. A second difference between what we did when we worked in population, and what we do when we work based on the actual data, pertains to the number of shocks we identify. Whereas when we worked in population it made sense to identify all of the seven shocks we consider, when we work with the actual data we regard as more sensible to leave one shock unidentified (in what follows we therefore do not impose any restriction to the column of the structural impact matrix at t=0 corresponding to this disturbance). The rationale for doing so is that it is highly implausible (and in fact essentially impossible) that the seven disturbances we consider are the *only* ones impacting upon real-world economies (as opposed to the theoretical model we considered in sub-sections 4.2-4.4). As a consequence, it makes sense to leave one unidentified disturbance as a 'catch-all' shock, which is going to 'hoover-up' the residual variance in the data over and above the six shocks we identify. In what follows we will therefore identify permanent IS and N shocks, and the first four shocks in Table 1 (sentiment, monetary, government spending, and transitory N).

Figures 5 and 6 show the fractions of forecast error variance at horizons up to 10 years ahead explained by the seven shocks, based on systems including the Conference Board overall index, and the University of Michigan's index of consumer sentiment pertaining to the question: *'Now turning to business conditions in the country as a whole—do you think that during the next 12 months we'll have good times financially, or bad times or what?'*[9] Figure 7 reports the same evidence from a different perspective, showing the estimated fractions of FEV jointly explained by permanent IS and N shocks, and the residual fractions of FEV, that is, the upper bound to the fractions of FEV pure sentiment shocks could explain in the implausible circumstance is which they were the *only other shock* driving the economy, beyond permanent IS and N shocks. The set of results reported in Figures 5-7 are representative of the overall set of results based on any of the confidence indices we consider. We only report results based on these two indices for reasons of space, but the full set of results is available upon request. Finally, we do not report the IRFs because they are not especially interesting, but they are all available upon request.

[9] Specificaly, as in Barsky and Sims (2012), the index we are using has been comouted as the difference between the 'Good times' and 'Bad times' percentages of answers.

The main substantive findings emerging from the three figures are that

first, the identified sentiment shocks explain small-to-negligible fractions of the FEV of all variables, including the confidence indices themselves, thus suggesting that measures of consumer confidence are driven, to a dominant extent, by disturbances other then pure sentiment. The only partial exception is represented by GDP at the very short horizons based on the Michigan index. In particular, for this series sentiment shocks explain (based on the median of the posterior distribution) about 40 per cent of the FEV on impact. It is to be noticed, however, the even based on this index, this is not the case for *all* of the other series in the system (including the confidence index).

Second, permanent IS and N shocks jointly explain very large to dominant fractions of the FEV of all series at the business-cycle frequencies[10] (which in the three figures are marked by the vertical blue lines), i.e., the frequencies the 'sentiment' literature has consistently focused upon (see e.g. ACD, 2018). Since, as discussed, (i) the presence of these two disturbances is essentially unquestioned in the macroeconomic profession; (ii) the way we identify them, *via* Uhlig's (2003, 2004) approach, is standard; and (iii) as mentioned, our restrictions allow to exactly recover the two shocks in population, the fact that these two shocks jointly explain large-to-dominant portions of the FEV of all variables at the business-cycle frequencies puts a robust upper bound on the role pure sentiment shocks might play. To put it differently, since permanent IS and N shocks are unquestionably there, and they play a large role in driving business-cycle fluctuations, even in the implausible circumstance in which sentiment shocks explained *all* of the residual FEV of macroeconomic variables not explained by IS and N shocks, this would not amount to much.

Our own conclusion is therefore that autonomous fluctuations in sentiment—even if they truly are there—play a minor-to-negligible role in macroeconomic fluctuations. This is in line with, e.g., Barsky and Sims' (2012) conclusion that *'[a]nimal spirits shocks account for negligible shares of the forecast error variances of consumption and output at all frequencies.'*, and with Feve and Guay's (2016) finding that the shock explaining the largest share of the residual forecast error variance of consumer confidence indices—once having preliminarily identified permanent technology shocks—explains very little of anything.

6 Conclusions

In this paper we have made two contributions to the literature exploring the role of sentiment in macroeconomic fluctuations. First, working with the theoretical MA representations of standard DSGE models, we have shown that several SVAR-based approaches to the identification of sentiment shocks are unreliable, as (e.g.) they

[10] In line with standard conventions in business-cycle analysis, the business-cycle frequency band is taken to be that associated with horizons between 6 and 32 quarters ahead.

identify such disturbances even when the model does not feature them. The approach proposed by Beaudry *et al.* (2011), for example, identifies sentiment shocks within Smets and Wouters' (2007) model. The problem is that the restrictions which are typically imposed are so weak and generic that they will always be satisfied with non-negligible probability by random rotations of the model's structural disturbances, irrespective of the fact that they do, or do not include a pure sentiment shock. Second, we have derived robust restrictions for the identification of sentiment shocks based on the model of Angeletos *et al.* (2018), and working with the theoretical MA representation of the model we have shown that they allow to recover the shocks' IRFs and fractions of forecast error variance either exactly, or with great precision. When we have imposed these restrictions upon the data within a structural VAR framework, we have consistently detected a minor-to-negligible role for sentiment shocks in business-cycle fluctuations.

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A The Data

A.1 Macroeconomic data

The following series are all available at the quarterly frequency:

- John Fernald's 'purified TFP' series is available from the San Francisco Fed's website.
- Real output per hour of all persons in the non-farm business sector (OPHNFB) is from the U.S. Bureau of Labor Statistics.
- A seasonally adjusted series for real GDP (GDPC96) is from the U.S. Department of Commerce: Bureau of Economic Analysis.
- Inflation has been computed as the log-difference of the GDP deflator (GDPCTPI) taken from the St. Louis Fed's website.
- Hours worked by all persons in the nonfarm business sector (HOANBS) is from the U.S. Department of Labor, Bureau of Labor Statistics.
- The seasonally adjusted series for real chain-weighted investment, consumption of non-durables and services, and their deflators (which we use in order to compute the chain-weighted relative price of investment) have been computed based on the data found in Tables 1.1.6, 1.1.6B, 1.1.6C, and 1.1.6D of the National Income and Product Accounts. Real consumption and its deflator pertain to non-durables and services. Real investment and its deflator have been computed by chain-weighting the relevant series pertaining to durable goods; private investment in structures, equipment, and residential investment; Federal national defense and non-defense gross investment; and State and local gross investment.

The remaining variables are available at a monthly frequency and have been converted to the quarterly frequency by taking averages within the quarter.

- The Federal funds rate and the 1-, 3-, 5-, and 10-year government bond yields are from the St. Louis Fed's website.
- is from the St. Louis Fed's website. It is quoted at a non-annualized rate in order to make their scale exactly comparable to that of inflation.[11]
- Civilian non-institutional population (CNP16OV) is from the U.S. Department of Labor, Bureau of Labor Statistics.

[11] If we define an interest rate series as R_t—with its scale such that, e.g., a ten per cent rate is represented as 10.0—the rescaled series is computed as r_t=(1+R_t/100)$^{1/4}$-1.

- The BAA-AAA spread is calculated from Moody's Seasoned Aaa Corporate Bond Yield (AAA) and Moody's Seasoned Baa Corporate Bond Yield (BAA) from the Board of Governors of the Federal Reserve System.

A.2 Confidence indices

Here follows a description of the consumer and CEO indices from the University of Michigan and the Conference Board.

A.2.1 Indices from the University of Michigan

From the website of the University of Michigan we took the following indices of consumer confidence. In what follows, for ease of reference, we refer to them as 'Index 1', 'Index 2', etc.

- *Index 1*: Overall Index
- *Index 2*: Current Index
- *Index 3*: Expected Index
- *Index 4*: Index Component 'Personal Finances, Expected'
- *Index 5*: Index Component 'Business Conditions 12 Months Ahead'
- *Index 6*: Index Component 'Business Conditions 5 Years Ahead'
- *Index 7*: The question was: 'Now looking ahead – do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?' (Computed as better off minus worse off)
- *Index 8*: The question was: 'During the last few months, have you heard of any favorable or unfavorable changes in business conditions? What did you hear?' (Computed as favorable news minus unfavorable news)
- *Index 9*: The question was: 'And how about a year from now, do you expect that in the country as a whole business conditions will be better, or worse than they are at present, or just about the same?' (Computed as better minus worse)
- *Index 10*: The question was: 'Now turning to business conditions in the country as a whole – do you think that during the next 12 months we'll have good times financially, or bad times or what?' (Computed as good times minus bad times)
- *Index 11*: The question was: 'Looking ahead, which would you say is more likely – that in the country as a whole we'll have continuous good times during the next 5 years or so, or that we will have periods of widespread unemployment or depression, or what?' (Computed as good times minus bad times)

Indices 1 to 3 are available since 1960Q1. Indices 4 to 7, 10, and 11 are available since 1959Q4. Index 8 is available since 1965Q1. Index 9 is available since 1965Q3.

A.2.2 Confidence indices from the Conference Board

Allen Li, of the Conference Board, has very kindly provided the following confidence indices. In what follows, for ease of reference, we refer to them as ‘Index 1’, ‘Index 2’, etc.

- *Index 1*: Consumer Confidence Index®: Overall index
- *Index 2*: Consumer Confidence Index®: Present Situation
- *Index 3*: Consumer Confidence Index®: Expectations
- *Index 4*: Measure of CEO Confidence™: Overall index
- *Index 5*: Measure of CEO Confidence™: Current Economic Conditions vs. 6 Months Ago
- *Index 6*: Measure of CEO Confidence™: Expectations for Economy, 6 Months Ahead
- *Index 7*: Measure of CEO Confidence™: Expectations for Own Industry 6 Months Ahead

Indices 1 to 3 are available since 1960Q1. Indices 4 to 7, 10, and 11 are available since 1959Q4. Index 8 is available since 1965Q1. Index 9 is available since 1965Q3.