Measuring the Effects of Expectations Shocks

Ana Beatriz Galvão; Michael P. Clements

University of Warwick; University of Reading

October 2019

Agents' Beliefs and Business Cycles

- Changes in agents' beliefs about the future may lead to business cycles (Pigou, 1927; Keynes, 1936).

Agents' Beliefs and Business Cycles

- Changes in agents' beliefs about the future may lead to business cycles (Pigou, 1927; Keynes, 1936).
- Waves of optimism and pessimism explained by frictional coordination caused by aggregate variation in higher-order beliefs (Angeletos, Collard and Dellas, 2018).

Agents' Beliefs and Business Cycles

- Changes in agents' beliefs about the future may lead to business cycles (Pigou, 1927; Keynes, 1936).
- Waves of optimism and pessimism explained by frictional coordination caused by aggregate variation in higher-order beliefs (Angeletos, Collard and Dellas, 2018).
- Confidence shocks explain a significant part of the business cycle variation (up to eight quarters ahead) in output, consumption, investment and hours, but have no effects on TFP, and only limited effects on inflation (Angeletos et al, 2018).

Agents' Beliefs and Business Cycles

- Evidence based on structural vector autoregressive models suggests that confidence (sentiment) shocks have a short term positive effect on economic activity (Barsky and Sims, 2012; Feve and Guay, 2018; Levchenko and Pandalai-Nayar, 2017).

Agents' Beliefs and Business Cycles

- Evidence based on structural vector autoregressive models suggests that confidence (sentiment) shocks have a short term positive effect on economic activity (Barsky and Sims, 2012; Feve and Guay, 2018; Levchenko and Pandalai-Nayar, 2017).
- Confidence shocks estimates rely on consumer confidence time series (Barsky and Sims, 2012).

Agents' Beliefs and Business Cycles

- Evidence based on structural vector autoregressive models suggests that confidence (sentiment) shocks have a short term positive effect on economic activity (Barsky and Sims, 2012; Feve and Guay, 2018; Levchenko and Pandalai-Nayar, 2017).
- Confidence shocks estimates rely on consumer confidence time series (Barsky and Sims, 2012).
- Some authors measure small effects (Feve and Guay, 2018), but others find large effects (Levchenko and Pandalai-Nayar, 2017).

Expectations Shocks

- We measure expectations shocks as the innovations to forecast revisions that cannot be explained by the updating of the information set of the forecaster (as in Leduc and Sill, 2013).

Expectations Shocks

- We measure expectations shocks as the innovations to forecast revisions that cannot be explained by the updating of the information set of the forecaster (as in Leduc and Sill, 2013).
- We show that empirical responses of macroeconomic variables to expectations shocks (if properly measured) are qualitative similar to the responses to confidence shocks (as in Angeletos et al, 2018) even if we purged effects of technological news and confidence shocks.

Expectations Shocks and Real-Time data

- To measure expectations shocks, we need to use data actually available for the economic agent at the time the expectation was formed (real-time data).

Expectations Shocks and Real-Time data

- To measure expectations shocks, we need to use data actually available for the economic agent at the time the expectation was formed (real-time data).
- We show that the real-time approach delivers consistent estimates of structural expectations shocks, which are otherwise confounded by data revisions if, as usually in the literature, the latest available vintage of data is employed.

Expectations Shocks and Real-Time data

- To measure expectations shocks, we need to use data actually available for the economic agent at the time the expectation was formed (real-time data).
- We show that the real-time approach delivers consistent estimates of structural expectations shocks, which are otherwise confounded by data revisions if, as usually in the literature, the latest available vintage of data is employed.
- To measure expectations shocks using GDP expectations surveyed every quarter, we employ a mixed-frequency VAR model to incorporate monthly data available in real-time.

Expectations Shocks and Real-Time data

- To measure expectations shocks, we need to use data actually available for the economic agent at the time the expectation was formed (real-time data).
- We show that the real-time approach delivers consistent estimates of structural expectations shocks, which are otherwise confounded by data revisions if, as usually in the literature, the latest available vintage of data is employed.
- To measure expectations shocks using GDP expectations surveyed every quarter, we employ a mixed-frequency VAR model to incorporate monthly data available in real-time.
- The mixed-frequency VAR delivers consistent estimates of expectations shocks and responses of earlier-released values to expectations shocks.

Dynamic Effects of Expectations Shocks

- Macroeconomists are typically interested in the impact of shocks on the *best estimates of key macroeconomic variables*, such as output, consumption, investment, hours, prices and TFP.

Dynamic Effects of Expectations Shocks

- Macroeconomists are typically interested in the impact of shocks on the *best estimates of key macroeconomic variables*, such as output, consumption, investment, hours, prices and TFP.

1. If we can assume that the true values of the macroeconomic variables are eventually observed after many rounds of revisions, then we can estimate the macroeconomist's VAR using the latest vintage of data but discarding observations still subject to many rounds of revisions.

Dynamic Effects of Expectations Shocks

- Macroeconomists are typically interested in the impact of shocks on the *best estimates of key macroeconomic variables*, such as output, consumption, investment, hours, prices and TFP.

1. If we can assume that the true values of the macroeconomic variables are eventually observed after many rounds of revisions, then we can estimate the macroeconomist's VAR using the latest vintage of data but discarding observations still subject to many rounds of revisions.
2. If true values are never observed, we show how to employ an instrumental variable approach, using past vintages as instruments, to estimate consistently the transmission of macroeconomic variables to expectations shocks using the macroeconomist's VAR.

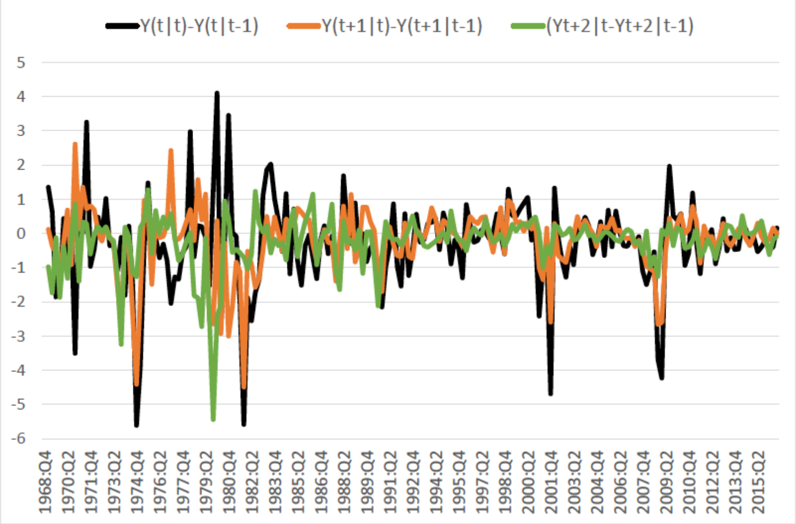
Expectations Updates/Revisions I

- We measure expectation shocks as the innovations to forecast revisions that cannot be explained by the updating of the information set of the forecaster.
- SPF forecasts are made around the middle of the middle month of the quarter. At quarter t, the value of the target variable Y_t is not available. In response to a survey at t, there is a nowcast $Y_{t|t}$ and forecasts for next three quarters $Y_{t+1|t}$, $Y_{t+2|t}$, $Y_{t+3|t}$. Forecasts revisions are:

$$Y_{t+n|t} - Y_{t+n|t-1},$$

  where $Y_{t+n|t}$ is the cross-sectional median of respondents' forecasts at time t of Y at $t+n$.
- We use the SPF forecasts for real GDP to compute forecasts for annualised quarterly GDP growth to avoid problems with real GDP rebasing (changes in deflator base year).

Characteristics of Expectations Updates I



Characteristics of Expectations Updates II

	$Y_{t\|t} - Y_{t\|t-1}$	$Y_{t+1\|t} - Y_{t+1\|t-1}$	$Y_{t+2\|t} - Y_{t+2\|t-1}$
Mean	-0.318	-0.210	-0.260
Median	-0.259	-0.066	-0.110
Std Dev	1.292	0.961	0.771
Corr with $Y_{t\|t} - Y_{t\|t-1}$	1		
Corr with $Y_{t+1\|t} - Y_{t+1\|t-1}$	0.479	1	
Corr with $Y_{t+2\|t} - Y_{t+2\|t-1}$	0.076	0.396	1

Nowcast updates $Y_{t|t} - Y_{t|t-1}$ are more likely than updates to longer-horizon forecasts. This might be because either output growth is stationary or forecasters tend to under-react to economic news (Bordalo et al, 2018). In either case, we use nowcast updates to capture short-run effects that may be linked to confidence.

Expectations Shocks and GDP Revisions I

- A forecast update at time t may be due to:
  1. new information that has arrived between $t-1$ and t
  2. sluggish adjustment to previous news due to inattentiveness or sticky information (see, e.g., Sims (2003), Mankiw and Reis (2002)), or
  3. changes in confidence (Barksy and Sims, 2012) and news about fundamentals (Beaudry and Portier, 2006).
- We aim to remove the effects of the first two possibilities by filtering forecast updates using a vector autoregressive model.

Expectations Shocks and GDP Revisions II

- At t, as forecasts are surveyed, the current GDP growth as in the current vintage, Y_t^{16Q4}, is not available due to a 30-day publication delay and data revisions.
- Forecasters are able to observe Y_{t-1}^{t}, that is, the first release of the last quarter and past observations.

Expectations Shocks and GDP Revisions III

- Assume for a moment that Y_{t-1}^{t} is the fundamental information released during the quarter, then the expectations shocks, assuming $p = 1$, are:

$$Y_{t|t} - Y_{t|t-1} = a_{11}(Y_{t-1|t-1} - Y_{t-1|t-2}) + a_{12}Y_{t-1}^{t} + u_t^{\exp}.$$

- But we also need a law of motion for fundamentals that will be release at the first month of next quarter:

$$Y_t^{t+1} = a_{21}(Y_{t-1|t-1} - Y_{t-1|t-2}) + a_{22}Y_{t-1}^{t} + a_{0,12}u_t^{\exp} + u_t^{fund}.$$

- The above identifies expectations shocks if $cov(u_t^{\exp}, u_t^{fund}) = 0$, which relies on the GDP publication delay.
- One could use the system of equations to measure the transmission of expectations shocks to fundamentals, assuming we are interested in the effects on their first-released values.

Expectations Shocks and GDP Revisions IV

- Assume the $t+s$ vintage (observed) estimate of the value of Y in period t, Y_t^{t+s}, where $s = 1, \ldots, l$, consists of the true value Y_t, as well as news and noise data revisions components, v_t^{t+s} and ω_t^{t+s}, so that

$$Y_t^{t+s} = Y_t + v_t^{t+s} + \omega_t^{t+s}.$$

Data revisions are news if the initially-released data is an optimal forecast of the revised data, so news revisions are not correlated with the earlier-release, i.e., $Cov\left(v_t^{t+s}, Y_t^{t+s}\right) = 0$. Data revisions are noise when each new release of the data is equal to the true value of Y_t, denoted Y_t, plus noise, so that noise revisions are not correlated with the truth, $Cov\left(\omega_t^{t+s}, y_t\right) = 0$.

Expectations Shocks and GDP Revisions V

- If the vintage of data currently available is Y_t^{T+1} for $t = 1, ..., T$, and T is large enough relative to the number of releases until the final values is observed such that $Y_t^{T+1} = Y_t$. Then the vintage-$T+1$ value incorporates all the l-news revisions terms, and has no measurement error, such that

$$Y_t^{t+1} = Y_t^{T+1} + v_t^{t+1} + \omega_t^{t+1}.$$

Expectations Shocks and GDP Revisions VI

- If we use the $T+1$ vintage of GDP in the first SVAR equation, we obtain:

$$\begin{aligned} Y_{t|t} - Y_{t|t-1} &= a_{11}(Y_{t-1|t-1} - Y_{t-1|t-2}) + a_{12}Y_{t-1}^{T+1} + \zeta_{1t} \\ \zeta_{1t} &= u_t^{\exp} + a_{12}\left(v_{t-1}^t + \omega_{t-1}^t\right). \end{aligned}$$

- The above implies that OLS won't deliver consistent estimates (endogeneity due to news revisions: $Cov(Y_{t-1}^{T+1}, v_{t-1}^t) \neq 0$ but $Cov(Y_{t-1}^{T+1}, \omega_{t-1}^t) = 0$) and we won't be able to recover expectations shocks, $u_t^{\exp}$.

Expectations Shocks and GDP Revisions VII

- If we estimate the first SVAR equation using real-time data to obtain $\hat{u}_t^{\mathrm{exp}}$, and then add the estimate shock to the second SVAR equation, but employ instead the $T+1$ vintage of GDP to estimate the parameters:

$$
\begin{aligned}
Y_t^{T+1} &= a_{21}(Y_{t-1|t-1} - Y_{t-1|t-2}) + a_{22}Y_{t-1}^{T+1} + a_{0,12}\hat{u}_t^{\mathrm{exp}} + \zeta_{2t} \\
\zeta_{2t} &= u_t^{fund} - (v_t^{t+1} + \omega_t^{t+1} - a_{22}\left(v_{t-1}^{t} + \omega_{t-1}^{t}\right)).
\end{aligned}
$$

  we also get inconsistent estimates due to news revisions.

Real-Time Mixed-Frequency VAR I

- At t, as forecasters are surveyed mid-quarter, monthly indicators on the current quarter are observed and their information employed to obtain $Y_{t|t}$. We use a mixed-frequency VAR, as in Ghysels (2016), to be able to capture their information.
- Monthly series may be also subject to revisions and publication delays as industrial production (IP) and employment (NP), which are included as $X_{t,m}^{t,m+1} = 100(\log(Z_{t,m}^{t,m+1}) - \log(Z_{t,m-1}^{t,m+1}))$. We use first releases for $IP_{t,m}^{t,m+1}$ and $NP_{t,m}^{t,m+1}$. In addition to IP and NP, we also consider stock returns (SP500), the short-rate and CPI inflation.

Real-Time Mixed-Frequency VAR II

- The identification of expectations shocks relies on the calendar of data releases. Monthly series are ordered as:

$$\mathbf{x}_{t,m}^{t,m+1} = [SP_{t,m}, R_{t,m}, IP_{t,m}^{t,m+1}, NP_{t,m}^{t,m+1}, \pi_{t,m},]'.$$

- And the 18-variable stacked mixed-frequency VAR is:

$$\mathbf{y}_t = [\mathbf{x}_{t,1}^{t,2\prime}, Y_{t|t}, Y_{t+1|t}, \mathbf{x}_{t,2}^{t,3\prime}, \mathbf{x}_{t,3}^{t+1,1\prime}, Y_t^{t+1}]'.$$

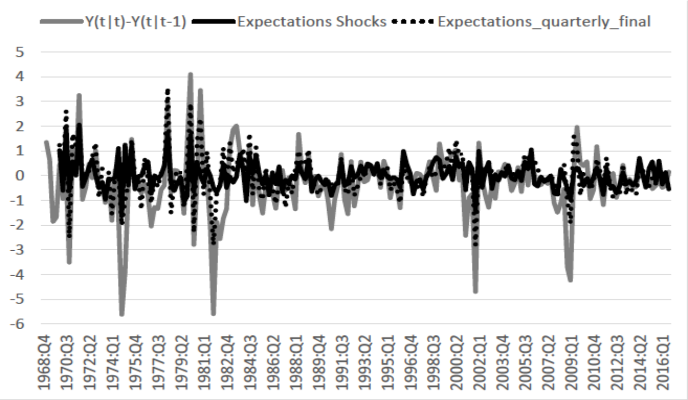
- The expectations shock is the sixth shock via recursive identification:

$$u_{t|t}^{\exp} = Y_{t|t} - E[Y_{t|t}|Y_{t|t-1}, \mathbf{x}_{t,1}^{t,2\prime}, \mathbf{x}_{t-1,2}^{t-1,3\prime}, \mathbf{x}_{t-1,3}^{t,1\prime}, Y_{t-1}^{t}, ...].$$

Real-Time Mixed-Frequency VAR III

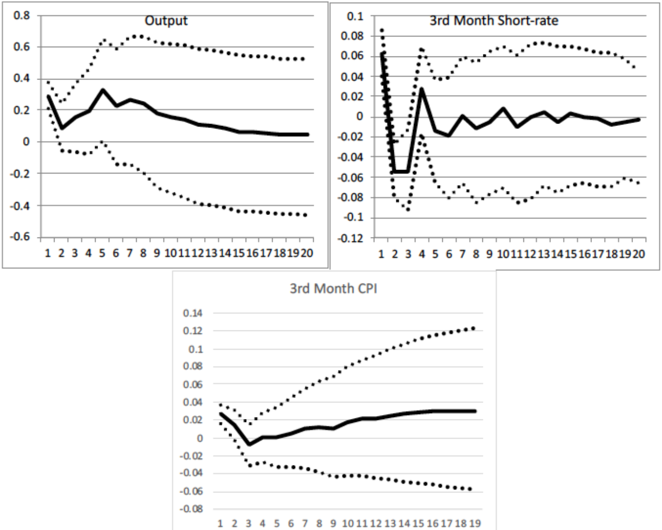
- Bayesian estimation as in Giannone, Lenza and Primiceri (2015); $p = 5$ with only the overall prior tightness for a Minnesota prior since VAR in differences. Estimation period: 1968Q4-2016Q3.
- The version of the model with latest available data ("final") uses Y_t^{16Q4} instead of Y_t^{t+1} and 2016M12 vintages for IP and NP.

The Expectations Shocks (at posterior mean) I

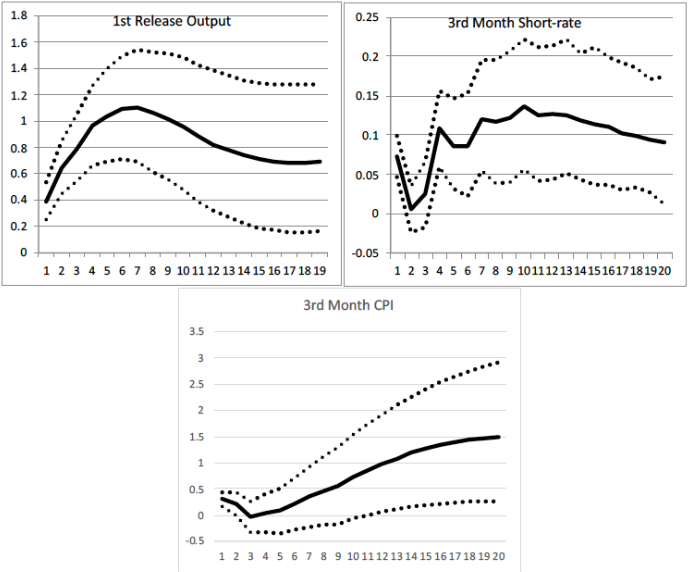


ES have a 53% correlation with expectations updates, but shocks are computed with quarterly and 2016Q4 data, we get a 76% correlation.

Mixed-Frequency VAR Responses to ES: 2016Q4 vintage



Real-time Mixed-Frequency VAR Responses to ES



Expectations Shocks Time Variation

- Large (2 std) shocks tend to occur during recessions or at turning points.
- They are more likely when there is a large disagreement across respondents, but disgreement explains only a small part of the variation of squared expectations shocks.

The Macroeconomist's VAR I

- The Macroeconomist's VAR includes a set of macroeconomic variables usually included to evaluate the impact of structural shocks (and as Forni et al, 2019). The values are in log-levels (Ramey, 2016) to capture long-run common components.
- The vector of endogenous variables is:

$$\mathbf{y}_t = [TFP_t, Inv_t, Cons_t, GDP_t, H_t, CPI_t, R_t]',$$

where TFP is the utilization-adjusted measure published by Fernald (2014).

The Macroeconomist's VAR II

- Our aim is to compute (for simplicity $p = 1$ and no intercept):

$$\mathbf{y}_t = \Phi \mathbf{y}_{t-1} + \mathbf{C}_0 \hat{u}_{t|t}^{\text{exp}} + \varepsilon_t.$$

- If true values are eventually observed $\mathbf{y}_t = \mathbf{y}_t^{T+1}$ for $t = p + 1, ..., T - l + 1$, then we can consistently estimate a VAR(p) model with $\hat{u}_{t|t}^{\text{exp}}$ as the first variable and compute responses under our previous assumption that expectations shocks are not correlated to fundamental shocks because of publication delays.

The Macroeconomist's VAR III

- If true values are not observed, but the expected revisions for $\mathbf{y}_t^{T+1}$ are only due measurement errors in the current release (as suggested by Croushore and Evans, 2006), then $y_{i,t}^{T+1} = y_{i,t} + \omega_{i,t}^{T+1}$ for $t = 1, ..., T-l+1$ and $i = 1, .., m$, and $l = 16$. The VAR is then:

$$\mathbf{y}_t^{T+1} = \Phi \mathbf{y}_{t-1}^{T+1} + \mathbf{C}_0 \hat{u}_{t|t}^{\exp} + \boldsymbol{\varepsilon}_t + \boldsymbol{\omega}_t^{T+1} - \Phi \boldsymbol{\omega}_{t-1}^{T+1},$$

  implying that disturbances are not orthogonal to regressors.
- An ealier vintage published at $T-l+2$ can be employed as instrument because they are different estimates of the same set of GDP observations (relevance) and their measurement errors are not correlated with the ones in the model disturbances ($E\left[\left(\varepsilon_{i,t} + \omega_{i,t}^{T+1} - \phi_i \omega_{i,t-1}^{T+1}\right)\left(y_{i,t-1} + \omega_{i,t-1}^{T-l+2} + v_{i,t-1}^{T-l+2}\right)\right] = 0$).

The Macroeconomist's VAR IV

- In practice, we first estimate the first-stage regressions for each variable subject to revision to obtain predicted values. The regressions are applied as:

$$y_{t,i}^{2016Q4} = \beta_{0,i} + \beta_{1,i}t + \beta_{2,i}t^2 + \beta_{3,i}y_{t,i}^{2013Q4} + \widetilde{\omega}_{i,t}$$

  for $t = 1968Q1, ..., 2012Q4$ and $i = 1, ..., 5$ (GDP, cons., inv., hours, TFP).

- Then we estimate:

$$\mathbf{z}_t = \mathbf{c} + \sum_{\tau=1}^{p} A_\tau \widehat{\mathbf{z}}_{t-\tau} + \mathbf{v}_t,$$

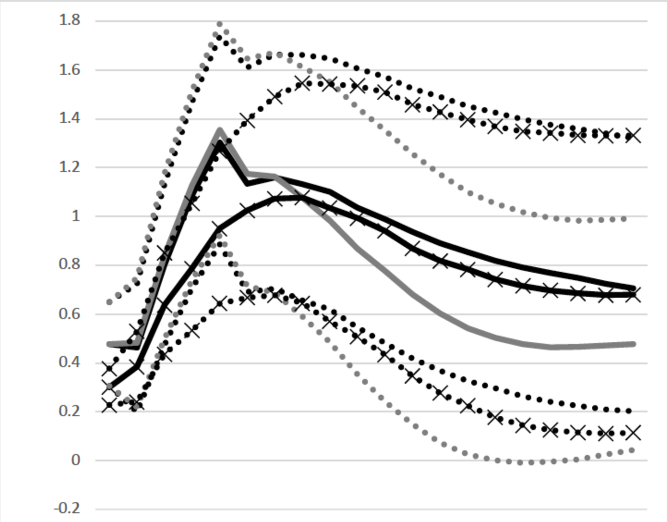
  $\mathbf{z}_t = [\hat{u}_{t|t}^{\exp}, \mathbf{x}_t']$ and $\widehat{\mathbf{z}}_t = [\hat{u}_{t|t}^{\exp}, \widehat{\mathbf{x}}_t']$.

The Macroeconomist's VAR V

- The VAR is estimated with 5 lags using the Minnesota prior and the 'dummy-initial-observation' prior with estimated hyperparameters (Giannone, Lenza, Primiceri, 2015).
- We compute responses and variance-decompositions using 20,000 draws from the posterior distribution and the recursive identification scheme.

Responses of Output to Expectations Shocks

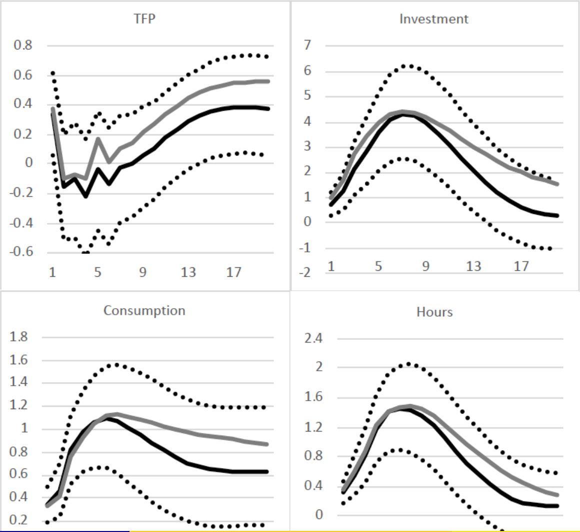
Figure 6: Responses of Output to expectations shocks: first-release (black_X) in the RT-VAR, in the macroeconomist VAR (black) and in the instrumented macroeconomist VAR (grey).



Variation of Output explained by Expectations Shocks

h	lower		upper
Real-time VAR – first-released output			
1	0.03	0.057	0.09
2	0.02	0.042	0.07
3	0.03	0.053	0.08
4	0.03	0.052	0.08
8	0.03	0.051	0.08
40	0.03	0.049	0.08
Macroeconomist VAR			
1	0.02	0.044	0.08
2	0.01	0.039	0.08
3	0.02	0.057	0.11
4	0.04	0.083	0.15
8	0.06	0.121	0.21
40	0.03	0.090	0.18
Instrumented Macroeconomist VAR			
1	0.02	0.045	0.08
2	0.02	0.040	0.08
3	0.02	0.060	0.11
4	0.04	0.086	0.15
8	0.06	0.119	0.20
40	0.03	0.076	0.15

Responses with the Instrumented Macroeconomist's VAR



Expectations Shocks: links with confidence and news shocks

- We compute news shocks as in Barsky and Sims (2011) and confidence shocks as Barksy and Sims (2012).
- We estimate a VAR with latest vintage values: $\mathbf{z}_t = [TFP_t, SP500_t, Conf_t, Y_t^{16Q4}, P_t, R_t]'$, then we identify new shocks by maximizing the FEDV of TFP after 40 quarters and by imposing that has zero effect at TFP at impact (orthogonal to technology surprises).
- We estimate a VAR with latest vintage values: $\mathbf{z}_t = [C_t^{16Q4}, Y_t^{16Q4}, Conf_t]'$, then we identify confidence shocks with a recursive scheme (confidence ordered last).

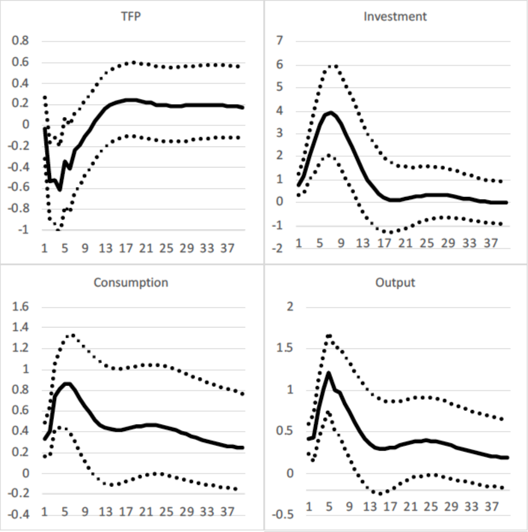
Correlation between ES and Alternatives

	$u^{exp}_{t\|t}, s_t$
$s_t = tfpnews_t$	0.158
	[1.524]
$s_t = consconf_t$	0.179**
	[2.321]
$s_t = u^{exp,final}_{t\|t}$	0.845***
	[19.59]

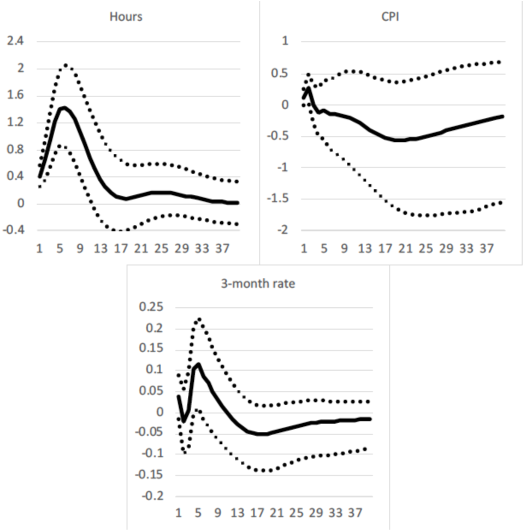
ES purged of Confidence/News effects

	$u_{t\|t}^{exp}$			$u_{t\|t}^{exp*}$			$u_{t\|t}^{exp}$			$u_{t\|t}^{exp*}$		
h	lower		upper	lower		Upper	lower		upper	lower		Upper
	Output						Consumption					
1	0.02	0.045	0.08	0.01	0.031	0.06	0.01	0.029	0.06	0.01	0.023	0.05
2	0.02	0.040	0.08	0.01	0.028	0.06	0.01	0.037	0.08	0.01	0.028	0.06
3	0.02	0.060	0.11	0.02	0.045	0.09	0.03	0.066	0.12	0.02	0.050	0.10
4	0.04	0.086	0.15	0.02	0.065	0.12	0.04	0.086	0.15	0.02	0.060	0.12
8	0.06	0.119	0.20	0.03	0.084	0.16	0.05	0.107	0.19	0.02	0.064	0.14
40	0.03	0.076	0.15	0.02	0.051	0.11	0.02	0.072	0.16	0.01	0.043	0.11
	Investment						Hours					
1	0.00	0.017	0.04	0.00	0.018	0.04	0.01	0.025	0.05	0.01	0.037	0.07
2	0.01	0.024	0.06	0.00	0.021	0.05	0.01	0.033	0.07	0.02	0.043	0.08
3	0.01	0.038	0.08	0.01	0.033	0.07	0.01	0.045	0.09	0.02	0.054	0.10
4	0.02	0.050	0.10	0.01	0.042	0.09	0.02	0.064	0.12	0.03	0.070	0.13
8	0.04	0.095	0.18	0.02	0.075	0.15	0.05	0.107	0.19	0.04	0.100	0.18
40	0.03	0.079	0.15	0.02	0.062	0.13	0.03	0.080	0.15	0.03	0.070	0.14

Responses to (purged) Expectations Shocks: I



Responses to (purged) Expectations Shocks: II



Effects of Expectations Shocks

- A comparison of our estimated responses with the ones computed for confidence shocks by Angeletos et al (2018) indicate qualitatively similar effects, since we find positive significant comovement in the key activity variables, and the effects on TFP, inflation and the short-rate, are very small.

Effects of Expectations Shocks

- A comparison of our estimated responses with the ones computed for confidence shocks by Angeletos et al (2018) indicate qualitatively similar effects, since we find positive significant comovement in the key activity variables, and the effects on TFP, inflation and the short-rate, are very small.
- However, consistent with Feve and Guay (2016) results on sentiment shocks, we find that expectations shocks explain a small part of the business cycle variation (around 10%) instead of the 40-60% reported by Angeletos et al (2018) using their model.

Conclusions

- To measure expectations shocks and their impact on the macroeconomy, the effects of data revisions need to be addressed as expectations are formed on the basis of early-release data which are subsequently revised.
- If expectations shocks are estimated on the latest-vintage of data, expectations shocks are contaminated by data revisions. The use of real-time data, coupled with higher-frequency information, allows the expectations shocks to be correctly estimated.
- The correct method to measure dynamic effects of expectations shocks on the macroeconomy depends on assumptions about the true values being eventually observed, and if effects are to be measured on either the first-releases or the true values.