This report builds on research I previously conducted during my MSc in Economics at Universidad Carlos III de Madrid. As part of my master's thesis, "Macroeconomic Effects of Consumer Confidence Shocks on the Spanish Economy: A Proxy-SVAR Approach", supervised by Juan José Dolado, I worked on a closely related project that extended empirical results from the literature on consumer confidence. During that period, Evi Pappa—one of the authors of the paper replicated here—was a professor at Carlos III, and she kindly granted me access to the relevant data (which is also publicly available).

The replications in this report are based on the code and empirical framework developed for my master's thesis, as well as on auxiliary files from Plagborg-Møller and Wolf (2022) and the VAR Toolbox by Cesa-Bianchi. This paper aligns closely with my research interests: although it is macroeconomic in nature, it directly engages with questions of human behavior, (ir)rationality, and belief formation, which are central to my broader academic agenda.

1. Introduction

Lagerborg et al. (2023), published in the Review of Economic Studies, tackles a fundamental question in macroeconomics: can autonomous changes in consumer sentiment—shifts in confidence unrelated to economic fundamentals—actually cause business cycle fluctuations? While the literature has extensively documented the causal effects of fundamental shocks like monetary policy changes, technology innovations, or oil price movements, there has been remarkably little direct empirical evidence on whether "animal spirits" or expectational errors independently drive economic activity. The central challenge lies in identification. Consumer confidence naturally fluctuates with economic conditions. People feel optimistic during booms and pessimistic during recessions. The difficulty is distinguishing whether confidence merely reflects information about fundamentals, and thus has no independent causal role, or whether autonomous sentiment shifts can themselves trigger recessions and expansions.

The authors address this challenge through an innovative instrumental variables approach, using fatalities from mass shootings as an external instrument to isolate exogenous variation in consumer sentiment. The paper employs sophisticated econometric techniques to estimate dynamic causal effects. The primary methodology is the Proxy Structural Vector Autoregression (Proxy-SVAR) estimator developed by Stock and Watson (2012) and Mertens and Ravn (2013), which allows researchers to identify structural shocks using external instruments. The authors also verify their findings using a Local Projection Instrumental Variables (LP-IV) method (Fieldhouse et al., 2018; Plagborg-Møller & Wolf, 2022; Ramey & Zubairy, 2018; Stock & Watson, 2018), which impose weaker assumptions than VARs, particularly regarding invertibility. That is, the assumption that shocks can be recovered from current and past observables alone.

The dataset spans January 1965 to November 2018, with a benchmark sample ending in August 2007 to exclude the Great Recession and the period when mass shootings became very frequent. The authors construct a novel database of mass shootings, combining and verifying information from three existing sources. They focus on incidents with seven or more fatalities that occurred in public spaces and were unrelated to gang activity or common crimes, yielding 42 events with 581 total fatalities over the benchmark period.

2. Methodological Framework & Code

The econometric approach rests on two key identifying assumptions. First, the relevance condition requires that mass shooting fatalities correlate with consumer confidence. The authors demonstrate this through first-stage F-statistics, which exceed conventional thresholds for instrument strength in their baseline specification (F-statistics of 11.6 and 19.3 for standard and robust versions). Second, the exogeneity condition requires that mass shootings be unrelated to other structural shocks and economic fundamentals. The authors argue that these tragic events, while receiving substantial media coverage and affecting psychological well-being across broad populations, have no direct macroeconomic costs and are not triggered by economic circumstances. The Proxy-SVAR specification includes seven variables: the Index of Consumer Expectations (ICE) from the University of Michigan Survey of Consumers, the unemployment rate, industrial production, the consumer price index, the federal funds rate, macroeconomic uncertainty, and real stock prices. All variables except the interest rate are detrended with fourth-order polynomials, and the VAR includes 18 monthly lags. Importantly, the paper also provides micro-level validation using individual survey responses.

Exploiting geographical variation, the authors show that mass shootings reduce consumer confidence significantly more for individuals residing in the county where shootings occur, even after controlling for time fixed effects, individual fixed effects, personal financial conditions, and local unemployment. This cross-sectional evidence supports both the relevance and exogeneity of the instrument.

The replication code implements the Proxy-SVAR estimation methodology. At the foundation is a standard VAR estimation framework implemented adapting the MATLAB VAR Toolbox (built on Ambrogio Cesa-Bianchi's VAR Toolbox 3.0). The function selectIC.m computes information criteria (AIC, BIC, and Hannan-Quinn) to determine optimal lag length selection by systematically estimating VARs for different lag specifications, calculating the variance-covariance matrix of residuals, and penalizing model complexity through standard information-theoretic formulas. This preliminary step ensures the VAR is properly specified before applying the instrumental variables identification strategy. The code uses 18 monthly lags as selected to maximize the first-stage F-statistic, balancing the need to capture dynamics with instrument strength.

The empirical analysis implements a Proxy-SVAR framework based on the identification strategy of Mertens and Ravn (2013). The core estimation routine, *doProxySVAR single trend.m*, first estimates the reduced-form VAR by OLS, regressing current values of the endogenous variables on their lagged values and deterministic components. Structural identification is then achieved using an external instrument for consumer confidence, exploiting its relevance for the confidence shock and its orthogonality to all other structural disturbances. The function recovers the contemporaneous impact vector by linking the reduced-form covariance matrix with correlations between VAR residuals and the instrument, following the algorithm proposed by Mertens and Ravn (2013).

Impulse responses are constructed by transforming the estimated VAR into its moving-average (MA) representation. This step is handled by *MARep.m*, which computes the MA coefficients required to trace the dynamic effects of a sentiment shock over long horizons. To conduct inference, the code relies on gradient matrices computed by *Gmatrices.m*, which map uncertainty in the estimated VAR parameters into uncertainty about impulse responses using the delta method.

Heteroskedasticity- and autocorrelation-consistent inference is implemented in *CovAhat Sigmahat Gamma.m*, which constructs the joint HAC covariance matrix for the VAR coefficients, the reduced-form residual covariance matrix, and the correlation between residuals and the external instrument. This procedure uses Newey–West standard errors via *NW hac STATA.m*, ensuring valid inference in the presence of serial correlation and time-varying volatility.

Given concerns about weak identification, the code implements several complementary inference approaches. Standard asymptotic confidence intervals are computed using the delta method in *doDeltaMethod.m*. Weak-instrument-robust confidence sets following Olea et al. (2021) are obtained through test inversion in *doMSWwivrobust.m*, which remains valid even when the instrument is weak. In addition, finite-sample robustness is assessed using a parametric bootstrap implemented in *doMSWbootstrap.m*, as well as a wild bootstrap procedure in *doProxySVARbootstrap single.m*, which is robust to conditional heteroskedasticity in the VAR residuals.

The analysis also incorporates methods from Plagborg-Møller and Wolf (2022) (auxiliary MATLAB files) to address potential non-invertibility and to compute forecast variance ratios. These procedures provide bounds on the contribution of sentiment shocks to macroeconomic fluctuations under weaker assumptions than standard VAR-based variance decompositions and are implemented using auxiliary routines adapted from their replication code.

Finally, the main workflow function *IRF proxy.m* orchestrates the estimation and inference pipeline, including sample selection, detrending, impulse response construction, and figure generation. A range of robustness checks is conducted using dedicated routines: *sensitivity large shoot.m* evaluates sensitivity to individual mass shooting events; *IRF IV placebo.m* performs placebo tests with reshuffled instruments; *IRF proxy NOtrend.m* and *IRF proxy month dummies.m* assess robustness to detrending and seasonality; and *IRF choleski.m* provides a comparison with recursive (Cholesky) identification based on timing assumptions.

3. Main Results

The empirical findings reveal that autonomous sentiment shocks have substantial and persistent real effects on the macroeconomy. Following a negative sentiment shock (normalized to a 1% decline in the ICE), consumer confidence falls significantly for 12-15 months, with only half the initial decline dissipating after eight months (see Figure 1). The recessionary impact on real activity is pronounced. Industrial production declines gradually but persistently, with the maximum decline occurring 7-12 months after the shock and remaining statistically significant at the 90% level for approximately 1.5 years (and at the 68% level for over two years). This demonstrates that autonomous shifts in sentiment translate into measurable contractions in aggregate output.

The labor market effects are particularly striking. The unemployment rate rises persistently[1], peaking 13-16 months after the sentiment shock and remaining significantly elevated for two years. The authors also find that labor market tightness (the vacancy-to-unemployment ratio) declines significantly for 15 months, driven by both rising unemployment and a substantial drop in firms' vacancy postings that persists for 16 months. These findings suggest that deteriorating sentiment affects both labor demand and labor market matching. Private consumption also contracts in response to negative sentiment shocks. Spending on non-durable goods falls significantly for over two years at the 90% confidence level, while durable goods spending also declines, though with larger standard errors[2]. This consumption response is consistent with the interpretation that sentiment shocks operate as demand shocks.

The nominal and financial market effects are more nuanced[3]. The short-term nominal interest rate declines persistently and significantly for 1.5-2 years, suggesting that monetary policy leans against the wind. Perhaps because of this monetary accommodation, the consumer price index shows only a small and short-lived response. Real stock prices decline but mostly insignificantly, which the authors attribute partly to the offsetting effects of the recession (negative) and lower real interest rates through monetary easing (positive). Counterfactual exercises suggest stock prices would have fallen much more substantially absent the monetary policy response.

Importantly, the identified sentiment shock appears distinct from other structural shocks. Total factor productivity (TFP) shows no significant response at any horizon, indicating that sentiment shocks are not simply mislabeled technology news shocks—a key alternative hypothesis examined by Barsky and Sims (2012). Macroeconomic uncertainty rises only briefly on impact, and the shock does not significantly affect the VIX or economic policy uncertainty measures (see Figure 3). These results help validate that the instrument truly isolates sentiment variation rather than capturing other fundamental disturbances.

The business cycle contribution of sentiment shocks is quantified using forecast variance

[1] See Figure 2 for the unemployment and the industrial production conclusions, and Figures 4, 5, 6, 7 as robustness checks.

[2] See Figure 3 to visualize the previous results.

[3] See Figures 2, 4, 5, 6, 7.

ratios (FVRs), which measure the reduction in forecast variance from knowing the shock sequence. The point estimates of upper bounds suggest sentiment shocks explain around 20% of fluctuations in consumer confidence at most horizons (rising to 30-40% at horizons below one year). For industrial production, sentiment shocks account for over 20% of variance at the 6-month to 1-year horizon and after two and a half years. For unemployment, the contribution reaches 20-30% at horizons between 6 months and 1 year. The 90% confidence intervals allow ruling out contributions above 30-40% for industrial production and unemployment at key business cycle frequencies. In contrast, sentiment shocks appear less important for asset markets and inflation.

These findings demonstrate that non-fundamental shocks to expectations can generate meaningful macroeconomic fluctuations, particularly in real activity and labor markets, supporting theories featuring coordination failures, incomplete information, or equilibrium indeterminacy where "animal spirits" matter for aggregate outcomes.

4. Replication

In this section, we present replications of the paper's main results discussed in the previous section. As noted earlier, the replication code (provided in a separate file) builds on the empirical framework I developed in MATLAB for my master's thesis, as well as on auxiliary files from Plagborg-Møller and Wolf (2022) and the VAR Toolbox by Cesa-Bianchi. Note that neither the LP-IV results nor those reported in the Supplementary Appendix have been replicated. The code replicates Table 1 (F-statistics for instrument relevance tests) and Figure 4 (historical realizations of sentiment shocks); however, these outputs are not included here to conserve space and to maintain focus on the replication of the main results.

Figure 1

Confidence (ICE) response to the instrument

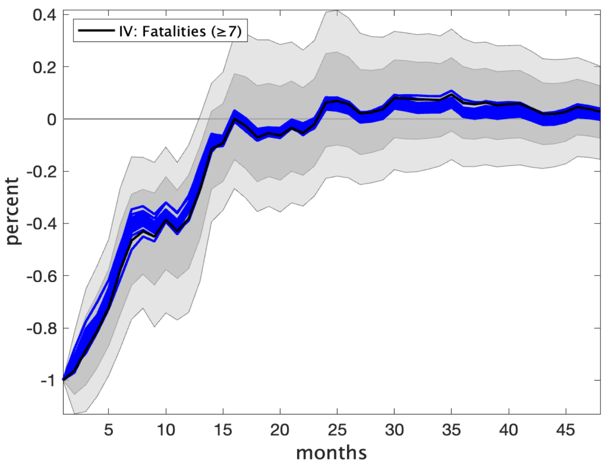


Figure 1 reproduces Figure 3 in Lagerborg et al. (2023). The solid black line shows the point estimate of the impulse response of ICE in the benchmark specification. Dark grey and light grey shaded areas denote 68% and 90% confidence bands, respectively, constructed using the weak-IV robust inference procedure of Olea et al. (2021). The blue lines report point estimates from alternative specifications in which each of the 24 mass shootings with seven or more fatalities is excluded one at a time, illustrating the robustness of the results to influential observations. The sample period is 1965:1–2007:8.

Figure 2 reports the impulse responses to a sentiment shock for the benchmark VAR specification, corresponding to Figure 5 in Lagerborg et al. (2023). The solid line represents point estimates, while the dark and light grey areas again indicate 68% and 90% confidence bands based on weak-IV robust standard errors following Olea et al. (2021). The sample period remains 1965:1–2007:8.

Figure 2

Consumer sentiment shock impulse responses—benchmark

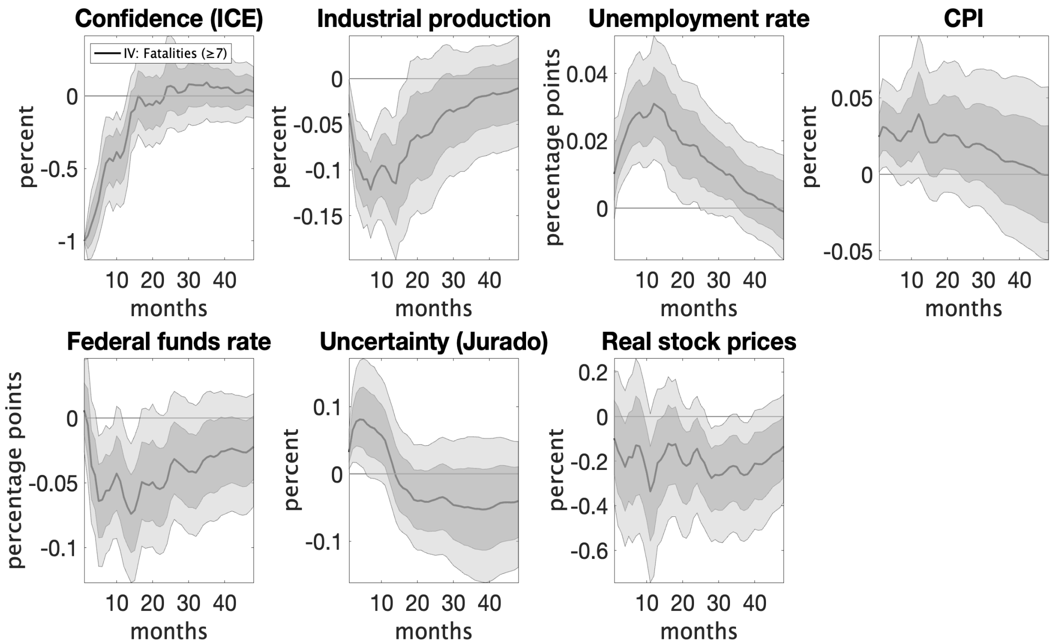
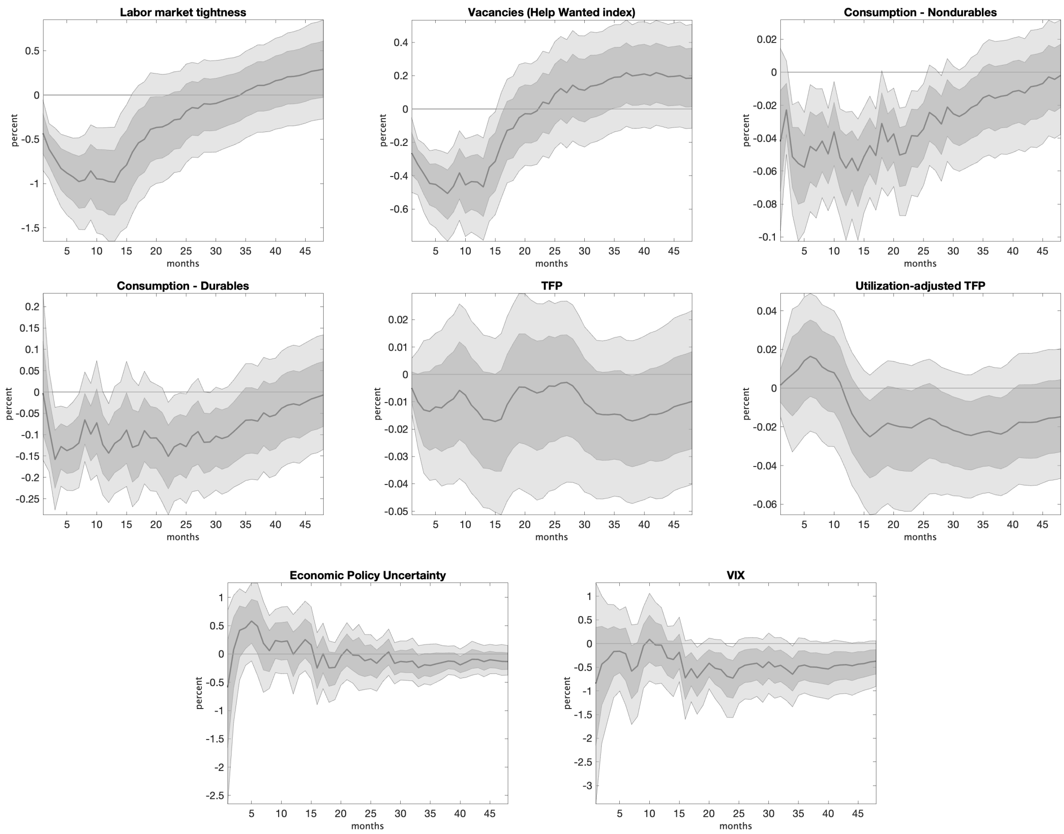


Figure 3

Consumer sentiment shock impulse responses—additional variables



To explore the effects of sentiment shocks on a broader set of macroeconomic aggregates, the authors augment the VAR by including additional variables one at a time. Figure 3 reproduces Figure 6 in Lagerborg et al. (2023) and displays the corresponding impulse response functions. As before, the solid line denotes point estimates, while dark and light grey bands represent 68% and 90% confidence intervals. In this case, inference is conducted using the parametric bootstrap procedure of Olea et al. (2021). The sample period is 1965:1–2007:8.

Figure 4 considers an alternative identification strategy in which mass shooting dummy variables, rather than fatalities, are used as the external instrument for ICE. This figure corresponds to Figure 7 in Lagerborg et al. (2023) and reports impulse responses for the sample period 1965m1–2007m8. The solid line shows point estimates, and the shaded areas denote 68% and 90% weak-IV robust confidence bands.

Figure 4

Alternative IV: mass shooting dummies, 1965m1–2007m8

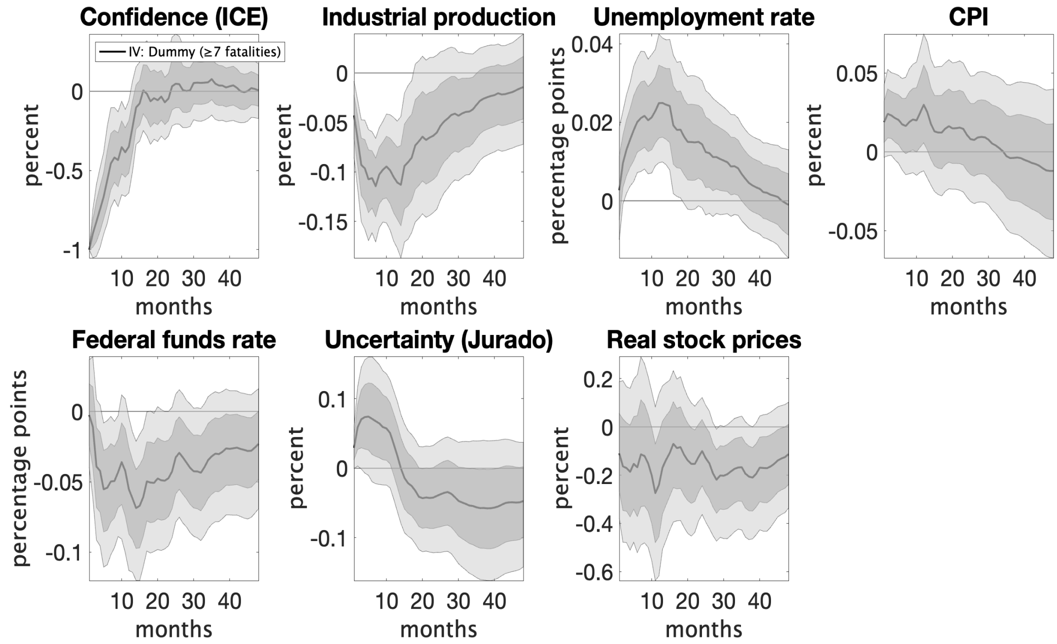


Figure 5

Alternative IV: mass shooting dummies, 1965m1–2018m11

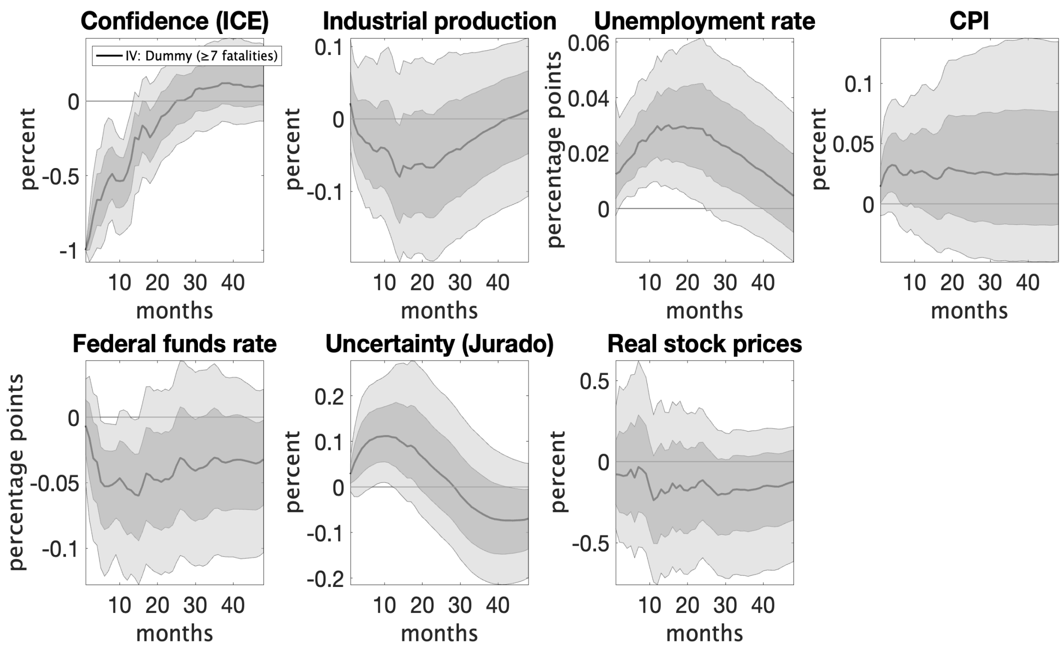


Figure 5 extends this analysis to a longer sample period, 1965m1–2018m11, and corresponds to Figure 8 in Lagerborg et al. (2023). The impulse responses are constructed using the same alternative IV strategy based on mass shooting dummies. As in previous figures, the solid line depicts point estimates and the shaded regions represent 68% and 90% confidence bands based on weak-IV robust inference (Olea et al., 2021).

To assess whether the results are driven by the specific timing of the external instrument, Figure 6 reports a placebo exercise corresponding to Figure 9 in Lagerborg et al. (2023). The figure plots the median impulse response, together with the 68% and 90% bands, across 10,000 replications in which the dates of mass shootings are randomly reshuffled. The absence of systematic responses in this placebo exercise supports the validity of the identification strategy.

Figure 6

Proxy-SVAR: placebo with reshuffled shootings

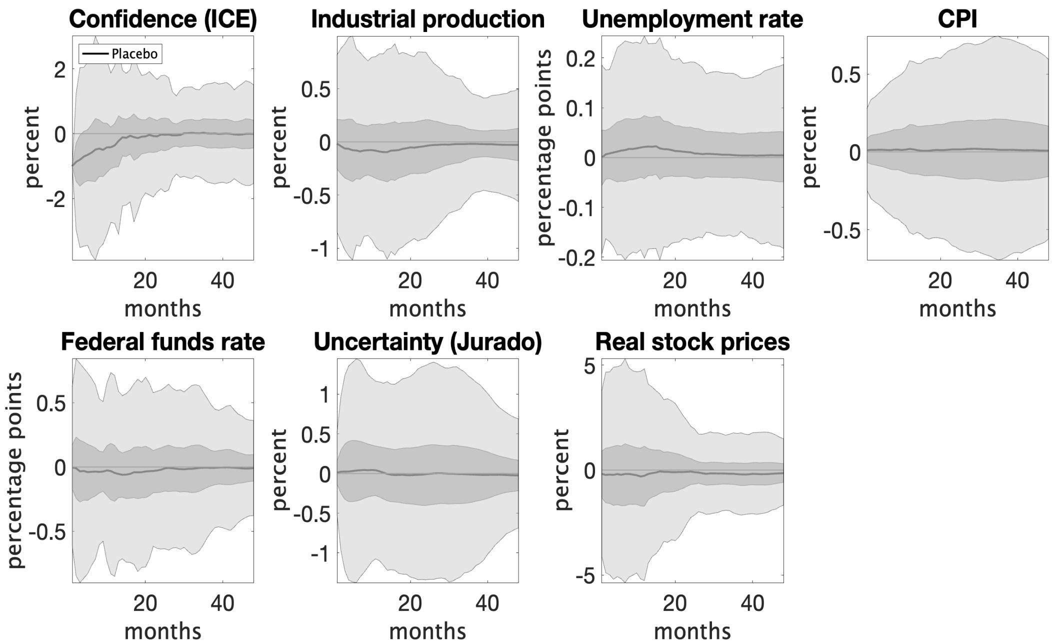
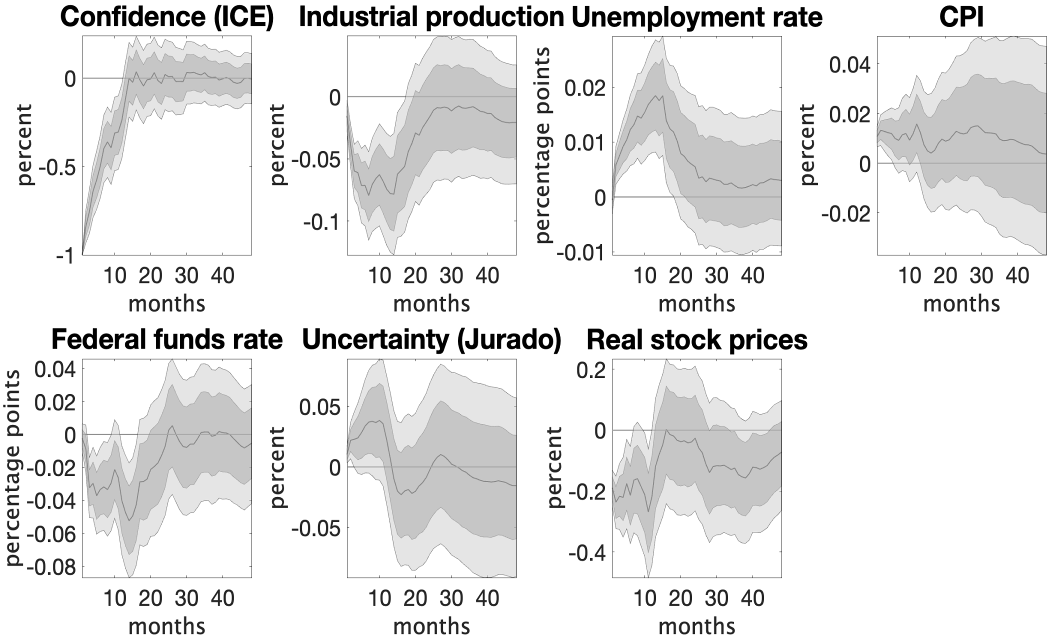


Figure 7

Cholesky SVAR—baseline variable responses



Finally, Figure 7 compares the proxy-SVAR results with those obtained from a conventional Cholesky SVAR identification based on a timing assumption, as in Barsky and Sims (2012). This figure corresponds to Figure 10 in Lagerborg et al. (2023). The impulse responses are identified by imposing a triangular structure on the covariance matrix. The solid line shows point estimates, while the dark and light grey areas represent 68% and 90% confidence bands. This comparison highlights the advantages of the external-instrument approach relative to standard recursive identification.

INCLUDE HERE FVRs FIGURES

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