Sentimental Business Cycles*

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Abstract

We use an IV framework to identify the dynamic causal effects of sentiment shocks on the aggregate U.S. economy. Using fatalities in mass shootings as our instrument, we demonstrate that autonomous declines in consumer confidence induce a rise in unemployment and fall in aggregate activity that is non deflationary and leads to a monetary expansion. Sentiment shocks explain a non-negligible part of cyclical fluctuations. We construct a theoretical framework of sentiment-driven cycles with heterogeneous agents, nominal rigidities and search-and-matching frictions, and estimate structural parameters with indirect inference. We argue that countercyclical endogenous income risk amplifies the impact of sentiment shocks.

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1 Introduction

An extensive empirical literature in macroeconomics has investigated the sources of impulses to the business cycle. The large majority of papers on this topic have addressed this question by providing causal evidence on the impact of "fundamental" shocks such as monetary and fiscal policy shocks, technology and investment-specific shocks, oil price shocks, credit shocks, uncertainty shocks, or shocks to labor supply (see the recent comprehensive survey of Ramey, 2016). However, under a variety of conditions, the economy may also be affected by non-fundamental shocks, such as expectational errors or 'animal spirits' but there is very little – if any – *direct* evidence on the impact of such shocks and their propagation. This paper provides empirical estimates of the causal effects of unexpected changes in consumer sentiments and relates the results to economic theory. We find that changes in consumer sentiments are an important source of impulses to the business cycles, especially for labor market indicators, and that their effects can be accounted for in settings where shocks to the economy are amplified through a countercyclical endogenous earnings risk channel.

The central challenge to estimating non-fundamental shocks and their causal effects is the translation of this concept into functions of observables. We address this by, first, focusing upon autonomous changes in consumer sentiments measured on the basis of variations in survey evidence on consumer expectations and, secondly, by assuming that news about events unrelated to fundamentals can be used for extracting movements in consumer expectations that are not simply responses to fundamental shocks. Operationally, we follow an extensive literature that has focused on the Index of Consumer Expectations (ICE) produced by the University of Michigan in its Survey of Consumer Confidence. The ICE contains information of survey respondents' views regarding the future outlook for their own and the U.S. economy's conditions, views that partially reflect the respondents' information about (current and future) fundamentals but which may also contain an autonomous component, consumer sentiments, the component we aim to identify.

We implement the Mertens and Ravn (2013) proxy SVAR estimator and propose to use fatalities in mass shootings in the U.S. to identify consumer sentiment shocks. The key idea is that such tragic events - while unrelated to economic fundamentals - may trigger a wave of pessimistic consumer sentiments which can impact on the economy. We focus on mass shootings with 7 or more fatalities which occurred in a public space and were unrelated to gang crime or to personal disputes. From 1965 to November 2018, there were no less than 619 fatalities in such shootings stemming from 46 separate events, with the most lethal ones being the 2017 Las Vegas Strip massacre (58 fatalities) and the 2016 Orlando nightclub massacre (49 fatalities). Notably the frequency and severity in terms of victims of mass shootings has increased with time; 20 percent of the total mass shootings (9 shootings) that resulted in almost 32 percent of total fatalities (197 fatalities) occurred in the last three years of the sample.

We study monthly data and focus on the sample period 1965:1 - 2007:8 - to exclude the period where shootings become very frequent with numerous victims and also the Great Recession - and our benchmark VAR consists of the ICE and macroeconomic aggregates (industrial production, civilian unemployment, the consumer price level, the short term nominal interest rate, a measure of macroeconomic uncertainty constructed by Jurado *et al.* (2015) and real stock market prices). Fatalities in mass shootings are used as a proxy for the autonomous changes in the ICE which we refer to as consumer sentiment shocks and we show that the proxy passes weak instrument tests. After a negative consumer sentiment shock, consumer confidence declines persistently and significantly so for around 15-18 months.

Deteriorations in consumer confidence triggered by a sentiment shock induce a rise in the civilian unemployment rate which remains significantly elevated for more than a year. The worsening labor market conditions are also reflected in reductions of hours worked, capacity utilization, labor market tightness and in vacancy postings. Accompanying the worsening labor market conditions, lower consumer confidence triggers a contraction in industrial production and in consumption of both non-durable and durable goods. The impact of the sentiment shock is less evident on financial market indicators. We do find a minor decline in short term nominal interest rates after a negative sentiment shock and a small and short-lived effect on CPI prices. Furthermore, stock prices and uncertainty, as well as utilization-adjusted TFP do not react significantly to the shock in sentiments at any horizon, implying that the identified shock is orthogonal to "news" and "uncertainty" shocks.[1] Confidence shocks explain a significant portion of cyclical fluctuations in consumer expectations, labor market indicators, industrial production and consumption, while it appears less relevant for variations in asset markets and in inflation. In particular, as much as 49 percent (36 percent) of the forecast error variance at the one year (four year) in the ICE derives from sentiment shocks while the corresponding numbers for unemployment and vacancies are 44 percent (25 percent) and 34 percent (17 percent), respectively. For industrial production, and consumption of non-durables, we find a contribution to the forecast error variance at the one year horizon of 25 percent and 37 percent, respectively.

We also investigate the extent to which such sentiment-driven cycles can be accounted for by theory. We examine an incomplete markets model with nominal rigidities and labor market matching in which agents have common but imperfect information about the source of shocks to the economy. In particular, in the model, technology is perturbed by persistent and transitory shocks but agents observe only their sum and a signal about the former. Using the Kalman filter to make inference about the two components, agents base their actions on the perceived components of technology. We then interpret sentiment shocks as the noise component of the signal. Embedding this in a heterogeneous agents model with frictions in labor and product markets is

[1]By contrast, using Cholesky zero short-run restrictions as an alternative identification strategy to uncover confidence shocks, we show that both stock prices and uncertainty measures as well as the utilization-adjusted TFP react significantly to the shock, highlighting a key difference between the Proxy-SVAR and Cholesky decompositions in the identification of pure " sentiment" shocks.

challenging but we make assumptions that facilitate the use of a first-order approximation due to limited equilibrium heterogeneity. The resulting model incorporates an endogenous earnings risk which can lead to amplification or stabilization of shocks to the economy depending on its cyclical properties. This risk channel derives from the impact of precautionary earnings risk on savings choices. When this wedge is countercyclical, precautionary savings increase in recessions which reduces goods demand over and above income reductions when unemployment is high, thereby amplifying the impact of shocks. A procyclical wedge, in contrast, is stabilizing. We estimate the deep parameters using a simulation estimator and the data suggest that the earnings risk wedge is countercyclical and amplifies the impact of sentiment shocks.

Our work adds to a long line of studies on the role of expectations and non-fundamental shocks for aggregate fluctuations dating back to at least Pigou (1926) and Keynes (1936). Recently, this literature has received a considerable amount of renewed interest, cf. Beaudry and Portier (2006), Beaudry and Lucke (2009), Beaudry *et al.* (2011), Lorenzoni (2009), Akerlof and Shiller (2009), Blanchard *et al.* (2013), Angeletos and La'O (2013), Angeletos *et al.* (2018) and Faccini and Melosi (2019). Our theoretical analysis builds on the imperfect information setup in Lorenzoni (2009) into which we introduce an amplification mechanism due to incomplete markets and unemployment risk. Angeletos *et al.* (2018) examine an alternative amplification mechanism through heterogeneity in preferences but focus mostly on short-run fluctuations. Faccini and Melosi (2019) focus on boom-bust cycles and estimate a general equilibrium model with non-pecuniary labor market frictions and noise shocks regarding future TFP growth. In their framework, the initial effects of noise shocks are very similar to those brought about by TFP news shocks, but when agents realize that their expectations are not going to materialize, they reduce investment and hiring and the economy goes through a persistent recession. We see our theoretical analysis as complementary to these papers.

The evidence from our estimated Proxy SVAR provides empirical support in favor of a causal effect of sentiment shocks. Our results are at odds with Barsky and Sims (2012) and Fève and Guay (2016), who find that animal spirit shocks have small and temporary effects on activity. Our findings instead agree with Lorenzoni (2009), Forni *et al.* (2017), Levchenko and Pandalai-Nayar (forthcoming) and Chahrour and Jurado (2018) who conclude that these shocks can have sizable and long-lasting macroeconomic effects. Relative to the previous studies, we seek direct evidence on the effects of sentiment shocks. Our work is also related to recent empirical studies that have tried to identify the macroeconomic effects of sentiment shocks in cross sectional studies. Mian *et al.* (2015) highlight that government policy sentiment shocks have limited effects on household's spending, while Benhabib and Spiegel (Forthcoming) and Makridis (2017) show that sentiments play an important role in propagating cycles in the economy, consistent with our results in the aggregate data.

The rest of the paper is organized as follows: the next section describes the data and the empirical framework. Section 3 presents our empirical results, while Section 4 presents the theoretical model, its estimation and its predictions. Finally, Section 5 concludes.

2 Data and Empirical Methodology

In this section we discuss the data and present the methodology we apply to derive causal estimates of the impact of sentiment shocks.

2.A Consumer Confidence

We study consumer confidence data collected by the University of Michigan's Survey of Consumer Confidence. This survey has been conducted since the late 1940's initially at the annual frequency, quarterly from 1952 and monthly from 1977. The long time span makes these data attractive for our purposes. We start our sample in 1965 and linearly interpolate the consumer confidence data prior to 1977 to produce a monthly series.

Each month approximately 500 randomly selected persons are surveyed by phone and asked a variety of questions regarding their own personal finances and about the economic and financial situation of the U.S. economy.[2] Answers are aggregated across respondents and across questions to produce three broad indices: the Index of Consumer Sentiment (ICS), the Index of Current Economic Conditions (ICC) and the Index of Consumer Expectations (ICE). The ICC focuses on answers to the questions that concern the current state of the respondents own financial situation and of the U.S. economy, the ICE is based upon forward-looking questions, while the ICS is a broad index covering respondents' views about both current and expected future conditions. We focus on the ICE because of its expectational nature.

The ICE summarizes responses to the following three questions:

1. "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?";

2. "Now turning to business conditions in the country as a whole–do you think that during the next twelve months we'll have good times financially, or bad times, or what?";

3. "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 five years or so, or that we will have periods of widespread unemployment or depression, or what?"

For each of these three questions, commonly referred to as PEXP, BUS12, and BUS5, respectively, the survey subjects choose between positive, neutral or negative answers. The index is then

[2] One third of the respondents are surveyed twice (with a six-month time interval in between) while the remaining one third of subjects are rotated monthly, which is likely to induce some sampling uncertainty.

computed as 100 plus the difference in the percentage of positive and negative respondents and the scores are normalized relative to the 1966 base period.

It is well documented that consumer confidence correlates with macroeconomic conditions. Figure 1 shows the time series of detrended ICE alongside industrial production and the unemployment rate. The ICE is correlated with industrial production and unemployment (the correlation coefficients are *0.33* and *-0.28*, respectively) and tends to peak, but not always, at the late stages of expansionary phases, reaching its trough just prior to economic recoveries. Further, Carroll *et al.* (1994) show that the ICS has predictive power for consumption growth (controlling for income); Matsusaka and Sbordone (1995) report that the ICS Granger causes GDP; Ludvigson (2004) shows that the independent information provided by consumer confidence predicts a small amount of additional variation in future consumer spending, when controlling for the consumption-wealth ratio. Such evidence, however, does not reveal whether consumer confidence variations derive from fundamental shocks (which may have predictive power for consumption and other variables) or whether autonomous shocks to consumer confidence influence the state of the economy. The IV framework proposed below aims at telling these two possibilities apart.

2.B Mass Shootings

We use fatalities in mass shootings as an instrument for shocks to consumer sentiments. The idea is that this constitutes a source of bad news which in itself should not derive from fundamentals. Our primary source for data on mass shootings in the U.S. is MotherJones (2019), a database which covers shootings with more than three fatalities in the period August 1982 up-to-date. We focus on mass shootings which had seven or more fatalities. We extend these data backwards to 1965 using information on mass shootings collected from Wikipedia (2018), news archives and an additional dataset constructed by Duwe (2007).[3] Following the methodology of MotherJones, we restrict attention to shootings where the motive appeared to be indiscriminate killings (i.e., not involving a personal motive such as gang crime or family disputes) that (i) were carried out with a gun by a lone shooter, (ii) occurred in a public place and (iii) involved more than 7 victims, excluding the perpetrator. Also included are a few cases known as "spree killings" in which the shootings occurred in more than one location in a short period of time but otherwise fitting the aforementioned criteria.

From January 1965 to November 2018, there were 46 such events with a total of 619 fatalities implying that each shooting on average had 13.5 fatalities.[4] Perhaps the two best known events are Columbine High in April 1999 where 12 students and 1 teacher were murdered and the Virginia Tech Massacre in 2007 when an undergraduate student murdered 32 people on campus.

[3]In the Online Appendix we show that our results are robust when using the alternative mass shootings recorded in Duwe (2007).

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The single worst mass shooting is the 2018 Las Vegas Strip Massacre in which 58 people were killed and 546 people were injured, followed by the Orlando Nightclub Massacre when 49 people lost their lives and 53 were seriously injured. Other very serious incidents cluster around those shootings, e.g. the San Bernandino Mass Shooting with 14 fatalities in December 2015 and the Texas First Baptist Church Massacre with 26 fatalities in November 2017.

Figure 2 illustrates the timeline of mass shootings over the whole sample, whereas the most serious incidents are listed in the Online Appendix. The frequency of mass shootings has increased over time from an average of one shooting every 1014 days prior to 1990, to one every 521 days between 1990 and 2000, and to one every 249 between 2000 and 2015, escalating to one shooting every 118 days in the last three years of the sample. Figure 2 also documents that the number of fatalities in mass shootings per month has increased in the last three years. Prior to 2015, each shooting involved on average 11.4 victims, a statistic which has increased to almost 23 per shooting since 2016. Given the increase in the frequency of shootings, we control for a trend in fatalities in mass shootings but the Appendix shows robustness to leaving out such a trend.

2.C Macroeconomic Aggregates

Our benchmark sample is January 1965 to August 2007 but we also examine results when including post-2007 data. The focus on the shorter sample is made for two main reasons. First, as highlighted above, the frequency of mass shootings increases significantly at the very end of the sample. As we discuss later, this has implications for the relevance of the instrument. Secondly, the Great Recession and its aftermath is likely to make the economy behave differently from other parts of the sample due to the depth of the recession, the lower floor on the short term nominal interest rate, etc. For that reason we use the sample 1965:1-2007:8 as our benchmark but in the Online appendix we report results for alternative sample periods and show that the results are robust to including post 2007:8 data although sampling uncertainty, as expected, increases.

The benchmark VAR includes as observables the civilian unemployment rate, industrial production, consumer price index, the federal funds rate as well as the short-term (12 months) uncertainty index of Jurado *et al.* (2015) and real stock prices (the Standard and Poors 500 index divided by the CPI). We also examine the impact on labor market indicators such hours worked per worker, vacancy postings, labor market tightness, on capacity utilization, as well as on consumption of non-durables and durables, respectively. In each case, we rotate these additional variables into the VAR one-by-one. Finally, we look at the relationship to news and other uncertainty shocks and study data on utilization-adjusted total factor productivity and economic policy uncertainty. The Online appendix includes precise definitions and sources for all the data.

2.D Methodology

We apply the proxy-SVAR estimator developed by Stock and Watson (2012) and by Mertens and Ravn (2013). The central idea is to use external instruments for the structural shocks of interest in a VAR setting. Here we adopt the notation of Stock and Watson (2018). Let $\mathbf{Y}_t$ be an $n \times 1$ vector of endogenous observables perturbed by an $n \times 1$ vector of structural shocks, $\mathbf{e}_t$, that we assume are mutually orthogonal. We assume that $\mathbf{Y}_t$ is second-order stationary and can be represented as:

$$\mathbf{A}\left(\mathbf{L}\right)\mathbf{Y}_t = \mathbf{u}_t \tag{1}$$

where $\mathbf{A}(\mathbf{L}) = \mathbf{I} - \mathbf{A}_1\mathbf{L} - \mathbf{A}_2\mathbf{L}^2 - \ldots$, and $\mathbf{L}$ is the lag operator, $\mathbf{L}^i\mathbf{x}_t = \mathbf{x}_{t-i}$. The innovations $\mathbf{u}_t$ are linear combinations of the structural shocks:

$$\mathbf{u}_t = \boldsymbol{\Theta}_0\mathbf{e}_t \tag{2}$$

where $\boldsymbol{\Theta}_0$ is invertible. Under the stationarity assumption, this implies that:

$$\mathbf{Y}_t = \Gamma\left(\mathbf{L}\right)\boldsymbol{\Theta}_0\mathbf{e}_t \tag{3}$$

where $\Gamma\left(\mathbf{L}\right) = \mathbf{A}\left(\mathbf{L}\right)^{\mathbf{-1}}$ is square summable. We are interested in characterizing the causal impact of a single shock and therefore in obtaining a single column of $\boldsymbol{\Theta}_0$. Without loss of generality, order consumer confidence first in the vector of observables. Let $\mathbf{s}_t$ be a proxy for $\mathbf{e}_{1t}$, the structural shock of interest. The proxy-SVAR then imposes the following identifying assumptions:

$$\mathbb{E}\left(\mathbf{s}_t\mathbf{e}_{1t}\right) = \phi \neq 0 \tag{4}$$

$$\mathbb{E}\left(\mathbf{s}_t\mathbf{e}_{it}\right) = 0,\ \ i > 1 \tag{5}$$

The identifying assumptions require correlation of the proxy with the unobserved structural shock of interest (the relevance condition in (4)) and orthogonality with other structural shocks (the exogeneity condition in equation (5)). Imposing the identifying assumptions implies that:

$$\mathbb{E}\left(\mathbf{s}_t\mathbf{u}_t\right) = \begin{pmatrix} \phi\boldsymbol{\Theta}_{0,11} \\ \phi\boldsymbol{\Theta}_{0,i1} \end{pmatrix},\ \ i > 1$$

where $\Theta_{0,ij}$ denotes the (i,j)'th entry of Θ_0.

Subject to the relevance and exogeneity assumptions, the dynamic causal effects of consumer sentiment shocks are identified up to a scale factor. We scale the impulse responses so that the sentiment shock corresponds to a one percent decline in the consumer confidence index, i.e.

$\Theta_{0,11} = 1$. The remaining structural coefficients of interest are then obtained as:

$$\frac{\mathbb{E}\left(\mathbf{s}_t \mathbf{u}_{i,t}\right)}{\mathbb{E}\left(\mathbf{s}_t \mathbf{u}_{1,t}\right)} = \mathbf{\Theta}_{0,i1}$$

We implement the estimator with a 2SLS procedure and estimate the coefficients above by regressing $\widehat{\mathbf{u}}_t$ on $\widehat{\mathbf{u}}_{1t}$ using $\mathbf{s}_t$ as the instrument. With these coefficients in hand, the impulse responses can be computed from equation (3). We compute standard errors guided on the evidence of instrument strength (with strong instruments, inference can be carried out using a Delta method estimator of the covariance matrix, else other covariance estimators are available, see Mertens and Ravn (2019) for a discussion).

3 Empirical Results

The benchmark specification of the vector of observables is:

$$\mathbf{Y}_t = [ic_t, u_t, ip_t, cpi_t, ff_t, unc_t, sp_t] \tag{6}$$

where ic_t is the log of ICE, u_t is the civilian unemployment rate, ip_t is log industrial production, cpi_t is the log of the consumer price index, ff_t is the federal funds rate, unc_t is the log of Jurado *et al.* (2015)'s 12-month uncertainty index, and sp_t represents the log of real stock prices. The VAR includes a constant and the lag length is set to 18 months.[5] We detrend all variables apart from the federal funds rate with fourth-order time polynomials and the sample period is 1965:1 - 2007:8. The Online appendix contains results for longer sample periods, alternative measures of confidence, and no detrending of the data.

3.A Mass Shooting Fatalities as an IV

Relevance

The underlying idea of the proxy is that mass shootings, while unrelated to fundamentals, can influence the economy because they may impact on households' views about the future path of the economy, views that are reflected in consumer sentiments. Mass shootings are likely to enter the information set of many households through news and through social interactions and therefore may possibly impact on behavior. There is direct evidence that mass shootings impact on psychological well being: Hughes *et al.* (2011) evaluate the impact of the Virginia Tech shooting in 2007 on post-traumatic stress disorder (PTSD) symptoms amongst Virginia Tech students in the months following the tragic event. They find that PTSD symptoms were elevated for an extended period even amongst students who were not under direct threat during

[5]This lag length is chosen to maximize the F-statistic, i.e the relevance criterion of our proxy instrument.

the shooting. Clark and Stancanelli (2017) document a decline in subjective well-being and an increased feeling of "meaningfulness" across the U.S. in the aftermath of the 2012 Sandy Hook School shooting and of the 2013 Boston Marathon Bombing. Furthermore, Fox and DeLateur (2013) show that, although mass shootings account for the fewest loss of lives compared to any other type of homicide, these events induce the most fear in people due to their seemingly random nature and the inability to predict and prevent incidents[6].

Mass shootings receive significant news coverage and are transmitted to a large portion of the U.S. population. For example, according to Lexis Nexis, a provider of electronic access to legal and journalistic documents, main national news sources in the U.S. printed no less than 182 articles on the Fort Hood Massacre in Texas in 2009 (which incurred in 13 fatalities) and 156 articles on the Newtown school shooting in Connecticut in 2012 (28 fatalities).[7] Lankford (2018) studies news coverage of the perpetrators of seven mass killings in the 2013-17 period and finds that mass killers received considerable news attention, in many cases more than celebrities such as sports stars. Towers *et al.* (2015) shows that mass killings are contagious in the U.S. through media coverage.[8]

The first row of Table 1 reports the outcomes of the first-stage F-statistics for the null hypothesis that the instrument has no explanatory power for consumer confidence in the baseline VAR. We report F-test statistics for a variety of specifications and for the null of standard conditional homoscedasticity (and no serial correlation), as well as the Montiel-Olea and Pflueger (2013) HAR-robust F-statistics. We first check the outcome of the weak instrument tests for the 1965:1 - 2007:8 sample, our benchmark. Next we include data up to end of 2015 and, finally, we look at the sample ending in November 2018.

For the 1965:1-2007:8 sample the standard F-statistic is equal to 11.3, while it is 17.6 when we correct for heteroscedasticity. The latter is much larger than the 5 percent critical value (3.84).

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[6]Terrorist attacks might also impact on psychological well-being (see, e.g. Lerner *et al.* (2003)). Policy institutions, such as the OECD have highlighted consumer confidence as a key transmission channel through which terrorist attacks impact the economy (e.g. Lenain *et al.* (2002)) and studies such as Abadie and Gardeazabal (2003) have shown that terrorism induces significant economic costs. Although terrorist attacks satisfy the relevance assumption, we do not consider them in our analysis since the exclusion restriction is arguably less credible. In particular, terrorism involves an inherently political form of violence, which might induce public fear of further attacks. This could possibly raise economic costs in terms of spending on policing and national security.

[7]These news sources constitute three of the highest-circulation national newspapers in the United States (Wall Street Journal, USA Today, and Washington Post) and one of the highest circulation newspapers in all four US census regions, including the Northeast (New York Times), South (Atlanta Journal Constitution), Midwest (Chicago Tribune) and the West (Los Angeles Times).

[8]Given the mechanism we want to highlight, we could use media coverage, instead of mass fatalities as the instrument for shootings. We have instead opted to use fatalities in mass shootings as the instrument in our baseline specifications, since this measure is arguably more objective and consistent throughout the sample period. Instead, media coverage data (e.g., Lexis Nexis, or Vanderbilt (2019) on tv coverage) is very noisy and given the fast developments in the communication sector the last two decades, it is hard to compare media coverage in the early years versus the later years of the sample. Notice that when we consider shootings with more than 7 fatalities, using media coverage measures and mass fatalities as instruments produces comparable results.

Adding data up to the end of 2015, the standard F-statistic remains approximately unchanged at 11.8 while the HAR version falls to 6.3 which is, nonetheless, still well above the 5 percent critical value. Going right up to November 2018 instead, both versions of the F-statistic decline and the HAR-robust F-statistic is only 2.4. The most likely reason for this is the stark increase in the frequency of the mass shootings at the end of the sample which makes it less reliable as an instrument, a point that we will show holds true in the model as well.

The MotherJones database also includes information on mass shootings with between three and six fatalities. In the second block of Table 1 we report the weak instrument tests for this alternative instrument for the sample period 1965:1-2007:8. This alternative instrument yields lower F-statistics but still passes the relevance test. The weaker correlation between this instrument and consumer confidence is probably caused by the more serious incidents attracting more attention.

Next we examine the relevance of the instrument when using alternative measures of consumer confidence. We consider the ICC, ICS, BUS5 and BUS12 that were discussed in Section 2 above.[9] In each case we use log transformations and detrend with fourth-order time polynomials. We find that fatalities in mass shootings remain useful as an instrument for the ICS while the instrument loses relevance when considering the ICC, i.e. consumers' perception of current circumstances. Focusing on the BUS12 and BUS5 indices, households' perception of the outlook for the US economy one and five years ahead, respectively, fatalities in mass shootings remain useful as a proxy for BUS12 but less so for BUS5. In other words, these events appear to impact on consumer perceptions of the near rather than the far future. The next rows in Table 1 report F-test values when we consider alternative specifications of the vector of observables, using inflation instead of CPI prices, and when we exclude the SP500 or U12 or both from the observables. None of these modifications alter the conclusions about relevance of the instrument.

The left panel of Figure 3 illustrates point estimates of the impact of the identified sentiment shock on the ICE based on the baseline VAR. The size of the shock is normalized so that consumer confidence falls by one percent on impact. We also show the 68 percent and 90 percent confidence intervals. Given the weak instrument test outcomes for our baseline specification, we could use the Delta method for computing confidence intervals. We opted to be more conservative and use the procedure suggested by Montiel-Olea *et al.* (2017) for inference, as this method is asymptotically valid in the face of weak instruments to treat all specifications presented in Table 1 equally. To further gauge robustness, we also report point estimates of the impulse response functions from specifications in which we exclude one-by-one each of the mass shootings with more than 10 fatalities to ensure that our results are not driven by particular events (which by chance could have been correlated with other shocks).

Figure 3 shows that the ICE falls persistently after a negative sentiment shock. Eight months

[9] We do not consider PEXP since the question relates to personal finances rather than the aggregate economic outlook.

after the drop in consumer confidence, only 50 percent of the initial drop has dissipated and it takes around 18 months before the point estimates of the drop in confidence has returned to its initial level. Taking sampling uncertainty into account, the decline in consumer confidence is significant for 13 months at the 90 percent level and for 15 months at the 68 percent level. The right panel of Figure 3 plots the responses of the ICE when we use shootings with more than 3 fatalities as the proxy. Again, the identified shock implies a drop in consumer confidence but it is less persistent and more imprecisely estimated than when we use the baseline proxy.

Exogeneity

The use of fatalities in mass shootings as an instrument for consumer sentiment shocks rests on the assumption that they are plausibly exogenous to other economic factors. Given the random nature of mass shootings, this is a plausible assumption. Pappa *et al.* (2019) show that mass shootings are not predictable by past economic conditions. Our identification strategy requires that they are orthogonal to current economic conditions. There is no compelling evidence that these events are triggered by prevailing conditions in the economy. In line with this, more than 60 percent of perpetrators have been diagnosed with signs of severe mental illness even prior to committing the mass shootings according to MotherJones (2019), suggesting that the mass shootings are carried out by individuals with serious pre-existing long-term mental health issues[10]. Finally, mass shootings occur with such a high frequency in the U.S. that it is unlikely that each individual event induces significant direct economic costs, giving additional credibility to the exclusion restriction.

One might also consider whether mass shootings could impact on macroeconomic aggregates directly, i.e. whether the channel goes through consumer sentiments.[11] Sadly, despite their tragic nature, as we have discussed earlier, mass shootings occur on a regular basis and each shooting is unlikely to trigger direct intervention (such as increased spending on security) which could question the exclusion restrictions we have imposed. It is also hard to imagine a direct impact on unemployment independently of the sentiment channel or that consumption would be impacted directly apart from possibly purchases of arms (which would tend to imply higher consumption expenditures which goes against our results discussed below).

[10]While some studies link economic recessions to mental health problems, an in-depth literature review conducted by Parmar *et al.* (2016) concludes that most studies were found to have substantial risk of bias and for that reason their results should be taken with caution. Nevertheless, even if such a link exists, effects on mental health were found primarily for women, while the vast majority (97.5 percent) of mass shooting perpetrators are men.

[11]Supporting our assumption that fatalities in mass shootings impact on the economy through consumer sentiments, we find fatalities to be a weak instrument for uncertainty and for stock prices.

3.B Dynamic Casual Effects

Sentiment shocks

Figure 4 presents point estimates and 68 and 90 percent confidence intervals (again based on the Montiel-Olea *et al.* (2017) parametric bootstrap) of the identified impulse responses based on the estimates deriving from the benchmark SVAR model for the 1965:1 - 2007:8 sample. The Online appendix contains the plots of the impulse responses for other samples.

An autonomous decline in consumer sentiments sets off a persistent deterioration in the economy. As discussed above, consumer confidence falls for around 13-18 months. In parallel with this, industrial production declines gradually but persistently with a one month delay reaching its largest fall around 8 months after the consumer sentiment shock. Unemployment also reacts with a hump-shape, reaching its peak 12 to 14 months after the drop in sentiments whereafter it starts to recover. The unemployment dynamics are very persistent and it takes more than two years for this indicator of the stance of the labor market to recover to its pre-shock level. On the monetary side, the negative consumer sentiment shock leads to a persistent rise in prices which is significant in the first couple of months but thereafter only at the 68 percent level and only for approximately a year.[12] The short-term nominal interest rate declines with a lag and remains below its initial level for more than 2 years. Turning to stock market prices, we find that the decline in consumer sentiments gives rise to a persistent drop in equity prices which is, however, statistically insignificant. Likewise, we find little evidence of a significant impact on macroeconomic uncertainty. At the 90 percent level, there is no impact on macroeconomic uncertainty at any forecast horizon; only at the 68 percent level, uncertainty rises in the first few months after the sentiment shock.

In order to explore aggregate consequences in some more detail we now introduce other variables into the VAR one at a time. Figure 5 illustrates the impact on real non-durables and durables consumption expenditures, respectively. The point estimates of the responses of consumer spending on non-durable and on durable consumption goods both decline after a negative consumer sentiment shock and both of these indicators of household spending remain significantly below trend for an extended period. Non-durables consumption falls on impact while the response of durable consumption is lagged. The peak decline in spending on durables is around two times larger than the corresponding number for spending on non-durables, yet, the response of non-durables consumption is much more persistent. Thus, the decline in aggregate activity produced by deteriorating consumer sentiments is associated with reduced consumption.

Figure 6 shows the impulse response functions of variables relating to the intensive margin of factor input use, hours worked per worker and capacity utilization, both of which decrease in response to worsening of consumer sentiments. Moreover, their responses are very similar and

[12]The initial rise in prices is robust across specifications, while the longer-term effects on the price level are more sensitive to the VAR specification.

appear to follow the path of the responses of industrial production. Of further interest is the impact on firms' hiring activities and on the overall state of the labor market looking beyond unemployment. Figure 7 shows that labor market tightness, the ratio of vacancy postings to unemployment, falls for a long period and significantly so for around 15 months following the worsening consumer sentiments. Moreover, we also find that the number of job vacancies posted by firms falls significantly for more than a year even at the 90 percent level. In summary, we find severe labor market ramifications of consumer sentiments.

Our results are qualitatively similar to those of Levchenko and Pandalai-Nayar (forthcoming) who identify confidence shocks in a quarterly VAR framework by assuming they are orthogonal to identified surprise and news TFP shocks and maximize the short-run forecast error variance of an expectational variable, such as a GDP forecast or the consumer confidence index. Like us, these authors find that an autonomous drop in consumer confidence sets about a decline in activity and in consumption along with a decline in nominal interest rates. The similarity in the qualitative results – despite the very different identification strategies – brings further credibility to our results.

Other shocks

An important check on our results is the extent to which the identified consumer sentiment shock may be confounded with other shocks. Barsky and Sims (2012) study the impact of innovations to consumer confidence using a Cholesky decomposition of the covariance matrix and argue, on the basis of a DSGE model, that the responses are consistent with consumer confidence innovations mainly reflecting news about future TFP.[13] Chahrour and Jurado (2018) show that news and noise information structures are observationally equivalent.

To check the relationship of the identified sentiment from the Proxy VAR shock with TFP and TFP news, we augment the vector of observables with the utilization-adjusted TFP series estimated by Fernald and Wang (2016). We find that TFP is unresponsive to the identified consumer sentiment shock (the response is statistically significant at the 68 percent level from 12 to 32 months after the sentiment shock but remains insignificant at all forecast horizons at the 90 percent level, see Figure 8). Hence, the identified sentiment shock is unlikely to be a news shock about TFP fundamentals. Along the same lines, it is interesting to relate the identified sentiment shock to an economic policy uncertainty shock since one might believe that mass shootings could signal periods of disputes between democrats and republicans. Similarly, mass shootings might be perceived to impact on future taxation due to an increase in spending in policing and security. In Figure 9 we also show that, if anything, mass shootings crowd out economic policy uncertainty (EPU), as measured by news coverage about policy-related economic uncertainty by Baker *et al.* (2016), consistent with the possibility that news coverage on mass shootings rises and thereby

[13]Note that these authors do not include TFP in their empirical VAR.

decreases the number of articles on other topics e.g. policy uncertainty. Moreover, uncertainty as measured by the VIX index of U.S. stock market options volatility is not significantly impacted, confirming that the sentiment shock we are capturing differs from other macroeconomic uncertainty shocks.[14] Moreover, we show in the Online appendix that our identified shock does not Granger cause the exogenous tax changes series of Romer and Romer (2010).

In order to stress the benefits of our identification procedure we present in Figure 10 the responses to a sentiment shock identified estimating a VAR for the same vector of observables and imposing a triangular structure on the covariance matrix as in Barsky and Sims (2012). Although responses of the macro variables look similar qualitatively with the ones presented in Figure 4, there are significant differences. The identified shock using the Cholesky decomposition induces a significant increase in uncertainty on impact and stock prices fall significantly for 8 months after the shock. Moreover, when we augment the model with utilization-adjusted TFP in Figure 11 also TFP falls significantly, while economic policy uncertainty and the VIX surge significantly on impact in Figure 12, suggesting that the identified innovations to confidence when using a Cholesky decomposition confounds sentiments with fundamental shocks.

Finally, in Figure 13 we run a placebo exercise in which we replace the proxy variable with randomly reshuffled mass shooting fatalities[15]. As expected, this proxy variable is a poor (insignificant) instrument for confidence and the responses of all observables turn out to be insignificant.

To sum up, our empirical results indicate that fatalities resulting from mass shootings in the US are a strong instrument for consumer sentiments and that a deterioration in sentiments is recessionary, non-deflationary, and persistent. We also show that a deterioration in consumer sentiments affects significantly the labor market variables, decreasing vacancies and increasing significantly labor market tightness.

Business cycle contribution

Table 2 reports the percentage of the forecast error variance (FEV) of a number of variables that can be accounted for by the sentiment shock for forecast horizons going from one month to 10 years.

Sentiment shocks explain a great deal of contemporaneous movements in confidence and at the one year to four year horizon, they explain between 36 percent to 49 percent of the FEV in the ICE. Even at the 10 year horizon, more than a quarter of the FEV of the ICE appears to derive from sentiment shocks. Thus, we find that sentiment shocks are an important source of variation in survey evidence on consumer expectations. Notice that since we find that the economy responds to declining consumer confidence, these variations in consumer confidence do

[14]This result remains robust whether we substitute U12 with the VIX in the VAR add it as an additional variable in the VAR.

[15]The reordering is drawn from a uniform averaged over 10,000 replications.

not have the interpretation of measurement errors or pure noise but rather indicate the share of the forecast error variance that is accounted for by non-fundamental shocks.

Consistently with the impulse response functions discussed above, sentiments also matter first order for fluctuations in the labor market explaining between 25 percent and 44 percent of the FEV of unemployment at forecast horizons from one to four years even at the 10 year horizon we find importance of this shock for unemployment. Likewise, sentiment shocks matter first-order for vacancy fluctuations accounting for 34 percent of the FEV at the one year horizon and 17 percent at the four year horizon. The contribution to variations in labor market tightness is smaller yet still close to 20 percent at the one and four year forecast horizons. The impact on the intensity of factor inputs is instead smaller apart from within the first 12 months.

Sentiment shocks also account for a non-trivial proportion of the FEV in industrial production and consumption expenditures. At the one year horizon, the benchmark VAR indicates that the sentiment shocks share of the FEV is 25 percent for industrial production, 37 percent for non-durables spending and 18 percent for durables expenditures; at the four year horizon, these numbers are 14, 38 and 20 percent, respectively. Thus, sentiment shocks appear to be particularly important for non-durables spending but also important for both industrial production and durables spending.

There is also some impact on the inflation rate but mainly at short forecast horizons up to six months where sentiment shocks account for 25-14 percent of the FEV. At long horizons, this source of variation seems of no consequence for inflation. Sentiment shocks also appear of little relevance to stock prices and to the Jurado et al (2015) measure of uncertainty.

The significant contribution of sentiment shocks to macroeconomic fluctuations that we find using the Proxy SVAR identification is consistent with the findings in other papers such as Blanchard *et al.* (2013) and Levchenko and Pandalai-Nayar (forthcoming) although the former of these finds a much larger contribution to consumption fluctuations at short forecast horizons and the latter finds a larger contribution to output fluctuations at short horizons than we do. These differences can derive from us studying higher frequency data or, more likely, from differences in the identification strategy with our analysis standing out in terms of providing direct evidence rather than relying more indirectly on moments of the data. However, each of these contributions agree on the fact that non-fundamental shocks appear to be an important source of impulse to the U.S. business cycle. Our results stress the importance for key labor market aggregates. Thus, our approach may identify a source of sentiment fluctuations that is more similar to the common factor driving labor highlighted by Hall and Schulhofer-Wohl (2017) than the asset market sentiments of Akerlof and Shiller (2009).

4 Theory

We study a heterogeneous agents model similar to Ravn and Sterk (2018) with uninsurable unemployment risk, rigid goods market prices and matching frictions in the labor market. This model generates an interaction between the supply side and the demand side of the economy which can lead to amplification or stabilization of shocks depending on key structural parameters which determine the cyclical variations in the precautionary savings motive. Following Lorenzoni (2009), we introduce imperfect common information into this setting. Firms in the economy are subject to transitory and persistent technology shocks but agents observe only their sum[16] in addition to a noisy public signal of true persistent productivity. When this latter signal is perturbed by noise, which we interpret as a sentiment shock, agents may confuse it with a change in persistent productivity which impacts on household choices and on firms behavior. We estimate key structural parameters and use the model to provide a fully structural interpretation of the empirical results and their consequences.

4.A The Model

Preferences: There is a continuum of measure one of infinitely lived households indexed by i who maximize expected discounted utility. Agents live in single-member households, consume a bundle of goods, $\mathbf{c}_i$, and face uninsurable unemployment risk. Preferences are given as:

$$\mathbf{U}_{i,s} = \widehat{\mathbb{E}}_s \sum_{h=0}^{\infty} \beta^h \frac{\mathbf{c}_{i,s+h}^{1-\mu} - 1}{1-\mu} \tag{7}$$

$\widehat{\mathbb{E}}_s x_{s+h}$ denotes the date s expectation of x_{s+h} given the information set available. The "$\hat{\ldots}$" on the expectations operator denotes that agents need to make inference about the true structural shocks given their information set. $\mathbf{c}$ is a CES aggregate over individual goods varieties:

$$\mathbf{c}_{i,s} = \left(\int_j \left(\mathbf{c}_{i,s}^j \right)^{1-1/\gamma} dj \right)^{1/(1-1/\gamma)} \tag{8}$$

where $\mathbf{c}_{i,s}^j$ is household i's consumption of goods variety j and $\gamma > 1$ is the elasticity of substitution between varieties. $\mathbf{n}_{i,s}$ denotes the household's employment status given as:

$$\mathbf{n}_{i,s} = \begin{cases} 0 & \text{if unemployed at date } s \\ 1 & \text{if employed at date } s \end{cases} \tag{9}$$

[16]Lorenzoni (2009) and Barsky and Sims (2012) focus on beliefs of productivity and income in the long run, we assume only temporary shocks in productivity that can be persistent or not.

Employed agents earn a real wage $\mathbf{w}_s$ while unemployed agents receive an endowment $\xi > 0$.[17] A currently unemployed worker finds a new job opportunity with probability $\eta_s \in (0,1)$.

Technology: There is a continuum of firms indexed by j each producing a unique goods variety, $\mathbf{y}_j$, by combining labor, $\mathbf{n}_j$, and effective capital, $\mathbf{z}_j\mathbf{k}_j$, the product of the input of capital, $\mathbf{k}_j$, and the capacity utilization rate, $\mathbf{z}_j$, according to a Cobb-Douglas technology:

$$\mathbf{y}_{j,s} = \exp\left(\mathbf{A}_s\right)\left(\mathbf{z}_{j,s}\mathbf{k}_{j,s}\right)^{\tau}\mathbf{n}_{j,s}^{1-\tau} \tag{10}$$

where $\mathbf{A}$ is an aggregate productivity shock and $0 < \tau < 1$ is the output elasticity to the input of effective capital.

Firms own the capital stock and the law of motion of the capital stock is:

$$\mathbf{k}_{j,s+1} = \left(1 - \delta\left(\mathbf{z}_{j,s}\right)\right)\mathbf{k}_{j,s} + \mathbf{i}_{j,s} \tag{11}$$

where $\mathbf{i}_{j,s}$ denotes investment in capital by firm j and $\delta\left(\mathbf{z}_{j,s}\right)$ is the capital depreciation rate. We assume that $\delta', \delta'' \geq 0$ so that higher capital utilization rates come at the cost of higher depreciation.

Firms hire labor in a matching market. At the end of each period, a fraction $\omega \in (0,1)$ of existing worker-firm matches are dissolved. New hires are made by posting vacancies, $\mathbf{v}_j$, at the flow cost $\kappa > 0$ per vacancy, per period. Each vacancy is filled with probability $\mathbf{q}$ which firms take for given. The vacancies are posted at the beginning of the period and filled prior to production. The law of motion of employment in firm j is given as:

$$\mathbf{n}_{j,s} = (1-\omega)\,\mathbf{n}_{j,s-1} + \mathbf{q}_s\mathbf{v}_{j,s} \tag{12}$$

The measure of new worker-firm matches, $\mathbf{m}$, is determined by a Cobb-Douglas matching function:

$$\mathbf{m}_s = \bar{m}\mathbf{u}_s^{\alpha}\mathbf{v}_s^{1-\alpha} \tag{13}$$

where $\mathbf{u}$ is the measure of unemployed workers, and $\mathbf{v} = \int \mathbf{v}_j dj$ is the measure of aggregate vacancies. $\bar{m} > 0$ is a constant and $0 < \alpha < 1$ denotes the elasticity of matches to the measure of unemployment. Letting $\theta = \mathbf{v}/\mathbf{u}$ denote labor market tightness, the job finding rate is given as:

$$\eta_s = \bar{m}^{1/\alpha}\mathbf{q}_s^{-(1-\alpha)/\alpha} = \bar{m}\theta_s^{1-\alpha}$$

Prices and Wages: Firms are monopolistically competitive and set the nominal price of their

[17] The fact that all employed workers earn the same real wage anticipates an assumption about wage determination that we make below.

product, $\mathbf{P}_j$, subject to quadratic price adjustment costs. They maximize the objective function:

$$\mathbf{\Phi}_{j,s} = \widehat{\mathbb{E}}_s \sum_{h=0}^{\infty} \mathbf{\Lambda}_{j,s,s+h} \left[\frac{\mathbf{P}_{j,s+h}}{\mathbf{P}_{s+h}} \mathbf{y}_{j,s+h} - \mathbf{w}_{s+h}\mathbf{n}_{j,s+h} - \mathbf{i}_{s+h} - \kappa \mathbf{v}_{j,s+h} - \frac{\phi}{2} \left(\frac{\mathbf{P}_{j,s+h}}{\mathbf{P}_{j,s+h-1}} - 1 \right)^2 \mathbf{y}_{s+h} \right] \tag{14}$$

where $\mathbf{\Lambda}_{j,s,s+h}$ denotes the stochastic discount factor of the owners of the firms, and $\mathbf{P}$ is the aggregate price level. $\phi \geq 0$ quantifies price adjustment costs, and $\mathbf{y} = \int \mathbf{y}_j dj$ is aggregate output. Firms maximize (14) subject to (10), (12) and

$$\mathbf{y}_{j,s} = \left(\frac{\mathbf{P}_{j,s}}{\mathbf{P}_s} \right)^{-\gamma} \mathbf{y}_s \tag{15}$$

We assume that the real wage is given as:

$$\mathbf{w}_s = \bar{w} \left(\frac{\eta_s}{\overline{\eta}} \right)^{\chi} \tag{16}$$

where $\bar{w}$,$\overline{\eta} > 0$ are constants.[18] This specification assumes that real wages respond to the job finding rate with an elasticity of χ, the idea being that real wages rise faster when workers are harder to hire. This assumption on the real wage determination simplifies the incomplete markets model substantially relative to assuming Nash bargaining.

Asset and Budget Constraints: Firms are owned by a small group of capitalists who hold equity portfolios while households only have access to the bond markets. Moreover, capitalists have no access to bond markets and are assumed not to participate in the labor market.[19]

Let $\mathbf{b}_{i,s}$ denote agents i's purchases of bonds at date s, $\mathbf{x}_{i,s}$ equity purchases, $\mathbf{R}_{s-1}$ the nominal interest rate, $\mathbf{R}_{x,s}$ the return on equity, and $\mathbf{\Pi}_s = \mathbf{P}_s/\mathbf{P}_{s-1}$ the gross inflation rate between periods $s-1$ and s. The flow budget constraint for capitalists is:

$$\mathbf{c}_{i,s} + \mathbf{x}_{i,s} \leq \xi + \frac{\mathbf{R}_{x,s}}{\mathbf{\Pi}_s} \mathbf{x}_{i,s-1} \tag{17}$$

and we assume that they cannot go short on equity:

$$\mathbf{x}_{i,s} \geq 0 \tag{18}$$

[18] Later we set these equal to the deterministic steady-state values of the real wage and the job finding rate, respectively.

[19] These assumptions can be micro-founded assuming limited participation in equity markets and the borrowing constraint below, see Ravn and Sterk (2018).

Workers face a sequence of budget constraints

$$\mathbf{c}_{i,s} + \mathbf{b}_{i,s} \leq \mathbf{w}_s \mathbf{n}_{i,s} + \xi\left(1 - \mathbf{n}_{i,s}\right) + \frac{\mathbf{R}_{s-1}}{\mathbf{\Pi}_s} \mathbf{b}_{i,s-1} \tag{19}$$

and the borrowing constraint:

$$\mathbf{b}_{i,s} \geq -\varkappa \mathbf{w}_s \mathbf{n}_{i,s} \tag{20}$$

Monetary Policy: The nominal interest rate is set by a central bank according to the interest rate rule:

$$\mathbf{R}_s = \mathbf{R}_{s-1}^{\delta_R} \left(\bar{R} \left(\frac{\mathbf{\Pi}_s}{\bar{\Pi}} \right)^{\delta_\Pi} \left(\frac{\theta_s}{\bar{\theta}} \right)^{\delta_\theta} \right)^{1-\delta_R} \exp\left(\varepsilon_s^R\right), \ \bar{R} \geq 1 \tag{21}$$

where $\bar{\Pi}$ is an inflation target, $\bar{\theta}$ denotes steady-state labor market tightness and $\varepsilon_{\mathbf{s}}^R$ is a monetary policy shock. $\delta_R \in [0,1)$ determines the amount of interest rate smoothing, δ_Π determines the response of the central bank to deviations of inflation from its target, and δ_θ determines the response to variations in labor market tightness. We allow the central bank to respond to labor market tightness because fluctuations in unemployment, due to the market incompleteness, can induce amplification of shocks.[20]

Information Structure and Stochastic Shocks: There are stochastic shocks to technology, to monetary policy and to expectations (sentiments). Similar to Lorenzoni (2009), the stochastic process for productivity is given as:

$$\mathbf{A}_s = \mathbf{A}_s^p + \varepsilon_s^T \tag{23}$$

$$\mathbf{A}_s^p = \rho_A \mathbf{A}_{s-1}^p + \varepsilon_s^P, \ \rho_A \in (-1, 1), \tag{24}$$

where $\mathbf{A}^p$ is a persistent component of productivity, ε^P is the innovation to this component, and ε^T is a transitory productivity shock. We assume that ε^P and ε^T are mutually orthogonal, normally distributed variables with means 0 and variances σ_T^2 and σ_P^2, respectively.

Agents observe $\mathbf{A}$ at the beginning of the period but not $\mathbf{A}_s^p$ and ε_s^T separately. Since expectations of future values of $\mathbf{A}_s$ depend on agents' perception of the current level of $\mathbf{A}_s^p$, agents therefore need to do signal extraction to form expectations of $\mathbf{A}_s^p$. We assume that this is accom-

[20]In experiments we do not present here for economy of space, we also allow for the possibility that the noise shocks impact directly on monetary policy. In that case, the innovation to monetary policy is given as:

$$\mathbf{e}_s = \varphi \varepsilon_s^S + \varepsilon_s^R \tag{22}$$

where ε_s^R is normally distributed with mean 0 and variance σ_R^2 and orthogonal to the other innovations in the economy. Agents observe $\mathbf{e}$ but not ε^R. When $\varphi = 0$, innovations to nominal interest rates reflect only the monetary policy shock ε_s^R while $\varphi \neq 0$ implies that innovations to interest rates are a mix of sentiments and pure monetary disturbances. When estimating the model using this specification for monetary policy, the estimate for parameter φ is zero. Results for this exercise are available from the authors upon request.

plished with a Kalman filter and that agents receive a signal about the persistent component of productivity:

$$\mathbf{\Psi}_s^A = \mathbf{A}_s^p + \varepsilon_s^S \tag{25}$$

where ε^S is assumed to be normally distributed with mean 0 and variance σ_S^2. ε^S is a noise shock that moves the expectations without affecting the realizations of the TFP disturbance, as it is orthogonal to the "fundamental shocks."

Letting $\mathbf{A}_{s,t}^P$ denote the date t expectation of $\mathbf{A}_s^P$, we have:

$$\mathbf{A}_{s,s}^p = \mathbf{G}\mathbf{A}_{s-1,s-1}^p + \mathbf{K}\mathbf{x}_s^o \tag{26}$$

where $\mathbf{x}_s^o = \left(\mathbf{A}_s, \mathbf{\Psi}_s^A\right)'$ is the vector of signals with the law of motion:

$$\mathbf{x}_s^o = \mathbf{C}\mathbf{A}_s^p + \mathbf{D}\varepsilon_s \tag{27}$$

see the appendix for details.

Equilibrium: The model displays limited heterogeneity in equilibrium. First, capitalists face no idiosyncratic risk and therefore have identical discount factors. Secondly, the unemployed workers would like to borrow but are prevented from doing so because of the borrowing constraint implying that they will not be on their Euler equation. Third, employed workers have an incentive to save due to unemployment risk and therefore are on their Euler equation because the borrowing constraint will not bind. We focus on the equilibrium properties of the model in the vicinity of the steady-state where $\bar{\Pi} = 1$, so that the central bank targets price stability. In the symmetric equilibrium, firms set the same prices and make the same investment, capacity utilization and employment decisions. The appendix summarizes the equilibrium conditions which we log-linearize around the steady-state and solve using the method of undetermined coefficients.

The combination of frictions in financial, goods and labor markets introduces an amplification mechanism (see Ravn and Sterk, 2018). Consider a log-linearization of the employed workers' Euler equation (and let $\bar{x}$ denote the steady-state value of x):

$$-(\mu\hat{\mathbf{c}}_s^e - \mu\beta\bar{R}\widehat{\mathbb{E}}_t\hat{\mathbf{c}}_{s+1}^e) = -\widehat{\mathbb{E}}_s\left(\hat{\mathbf{R}}_s - \hat{\mathbf{\Pi}}_{s+1}\right) + \beta\bar{R}\Psi\widehat{\mathbb{E}}_s\hat{\eta}_{s+1}$$

where $\Psi = \omega\bar{\eta}\left[\left(\left(\frac{\xi}{\overline{w}}\right)^{-\mu} - 1\right) - \chi\mu\left(1-\bar{\eta}\right)/\bar{\eta}\right]$.

This Euler equation differs from its complete markets version because of (i) discounting since future consumption enters with the coefficient $\mu\beta\bar{R} < \mu$; and (ii) because of precautionary savings through the last term on the right hand side which represents an endogenous earnings risk wedge. The impact of the job finding rate on the consumption path depends on the parameter Ψ which may be positive or negative. Large consumption losses in case of job loss (low ξ relative to $\overline{w}$) combined with risk aversion ($\mu > 0$) will tend to make Ψ positive which we will refer to as countercyclical earnings risk while very elastic real wages (large χ) will tend to make Ψ negative (procyclical earnings risk).

Consider the case of countercyclical earnings risk, $\Psi > 0$. In this case, when jobs are hard to find, employed households have an incentive to increase savings for precautionary reasons because of the risk of unemployment. Reversely, when $\Psi < 0$, households save for precautionary reasons in booms because wages are very procyclical. In the former case, goods demand declines in recessions which leads firms to cut vacancy postings reinforcing the precautionary savings motive and therefore introducing amplification. When earnings risk is procyclical, goods demand declines for precautionary savings reasons in booms which stabilizes the impact of shocks on the economy. Hence, this parameter will be a key object of our estimation exercise.

Sentimental Business Cycles

Estimation: We estimate key structural parameters using a simulation estimator. Initially, we split the vector of structural parameters into Θ_1 and Θ_2. Θ_1 contains structural parameters that we calibrate rather than formally estimate and we discuss these below. Θ_2 is the vector of parameters that we estimate.

Formally, Θ_2 is found by solving a quadratic minimization problem:

$$\widehat{\Theta}_2 = \arg\min_{\Theta_2} \left[\left(\widehat{\Lambda}_T^d - \Lambda_T^m \left(\Theta_2 | \Theta_1 \right) \right)' \mathbf{W} \left(\widehat{\Lambda}_T^d - \Lambda_T^m \left(\Theta_2 | \Theta_1 \right) \right) \right] \tag{28}$$

where $\widehat{\Lambda}_T^d$ denotes a vector of moments that we aim at matching, $\Lambda_T^m \left(\Theta_2 | \Theta_1 \right)$ are the equivalent moments from the theoretical model, and $\mathbf{W}$ is a weighting matrix. We include in the vector of moments that we match (i) the $F-$statistic from the first-stage regression of the proxy SVAR model estimated earlier, (ii) the standard deviation of (detrended TFP), and (iii) the impulse responses of consumer confidence, output, unemployment, the price level and the nominal interest rate in response to a sentiment shock for a forecast horizon of 36 months. The $F-$statistic is included because it helps identifying the measurement error that we discuss below. The standard deviation of TFP is included because it matters for the weights in the Kalman filter and, therefore, the impact of noise shocks. We obtain estimates of capacity non-adjusted TFP from Fernald (2012) and we detrend this series with a fourth-order time polynomial. This delivers an estimate of the standard deviation of TFP of 3.3 percent per month.

We find the impulse responses from the model by estimating proxy-SVARs on artificial data generated by the model. We estimate a VAR with 5 observables: consumer confidence, industrial output, unemployment, inflation and the nominal interest rate. The latter four of these have natural counterparts in the model[21]. As far as consumer confidence is concerned, we follow

[21] The baseline empirical model presented in the previous section includes also stock prices and macroeco-

Barsky and Sims (2012) and assume that consumer confidence is given as:

$$\mathbf{CI}_s = (1 - \rho_{CI})\,\bar{\mathbf{CI}} + \rho_{CI}\mathbf{CI}_{s-1} + \mathbf{e}_{CI,s} \tag{29}$$

$$\mathbf{e}_{CI,s} = \vartheta_1\left(\mathbf{A}_s - \rho_A\mathbf{A}^P_{s-1,s-1}\right) + \vartheta_2\left(\mathbf{A}^P_{s,s} - \rho_A\mathbf{A}^P_{s-1,s-1}\right) + \varepsilon_{CI,s} \tag{30}$$

where $\rho_{CI} \in (-1, 1)$ is the persistence of consumer confidence measure, and $\varepsilon_{CI,s}$ is a normally distributed random variable with mean zero and variance σ^2_C which is orthogonal to other innovations. Equation (30) implies that consumer confidence improves when current productivity exceeds the Kalman filter forecast from the previous period and when agents' estimate of the level persistent component of productivity is above last periods estimate. We then use a noisy measure of the sentiment shocks as the instrument for $\mathbf{CI}_s$ and derive the estimates of the relevant moments.

The model equivalents of the empirical impulse responses are generated as follows. Start with a guess on Θ_2, Θ^0_2:

1. Given Θ_1 and Θ^0_2, generate 200 sequences of artificial data from the model for sample periods of $T + R$ observations (where T is the number of observations in the sample that we used to estimate $\widehat{\Lambda}^d_T$). Eliminate the first R observations. Denote this $T \times 5$ vector of the model-based observables for the j'th artificial sample by $\tilde{X}_j\left(\Theta^0_2|\Theta_1\right)$. For each sample, let $\tilde{\varepsilon}^S_j\left(\Theta^0_2|\Theta_1\right)$ denote the $T \times 1$ vector of sentiment shocks.

2. Add a small amount of measurement error to $\tilde{X}_j\left(\Theta^0_2|\Theta_1\right)$. Let $\widehat{X}^j\left(\Theta^0_2|\Theta_1\right)$ denote the resulting artificial samples of X. Detrend the artificial data with a fourth-order time polynomial as in the data.

3. Add measurement error to $\tilde{\varepsilon}^S_j\left(\Theta^0_2|\Theta_1\right)$ to obtain $\widehat{\varepsilon}^S_j\left(\Theta^0_2|\Theta_1\right) = \tilde{\varepsilon}^S_j\left(\Theta^0_2|\Theta_1\right) + m_j$ where m_j is assumed to be normally distributed with mean zero and variance σ^2_m. From this form the vector $\varepsilon^{*S}_j\left(\Theta_2|\Theta_1\right)$ where $\varepsilon^{*S}_j\left(\Theta^0_2|\Theta_1\right) = \widehat{\varepsilon}^S_j\left(\Theta^0_2|\Theta_1\right)$ for the M largest (absolute) values of $\left[\widehat{\varepsilon}^S_{ji}\left(\Theta^0_2|\Theta_1\right)\right]^T_{i=1}$ and zero otherwise where M is chosen to be the same as the number of shootings in the data.

4. For each artificial dataset, estimate the model equivalents of the empirical proxy-SVAR moments using $\varepsilon^{*S}_j\left(\Theta^0_2|\Theta_1\right)$ as an instrument for $\mathbf{CI}_j\left(\Theta^0_2|\Theta_1\right)$. Let $\Lambda^m_T\left(\Theta^0_2|\Theta_1\right)^j$ denote the simulated equivalents of the vector of empirical moments for the j'th artificial sample.

5. Average the moments over the 200 replications, yielding $\Lambda^m_T\left(\Theta^0_2|\Theta_1\right)$.

nomic volatility in the vector of observables. Since we do not model theoretical counterparts for these variables one would worry that data and theoretical responses are not comparable and the model suffers from invertibility issues. In the Online Appendix we show that the estimated impulse responses of a five-variable VAR are not significantly different from the responses of our baseline empirical model.

6. Evaluate the loss function (28). If this is smaller than ε^{crit} let $\widehat{\Theta}_2 = \Theta_2^0$. Otherwise update guess for Θ_2^0 and return to step 1.

The measurement error that we add in Step 2 is introduced solely to avoid stochastic singularity of the VAR estimated on the artificial data given that the model features four shocks while there are five observables. We calibrate this source of measurement error. The measurement error added in Step 3, instead, is introduced in order to match the $F-$statistic of the first stage regressions. The further selection of the M largest values of the noise shock as the instrument is meant to emulate the fact that we use fatalities in the M most dramatic shootings in the data as the instrument for consumer confidence in the data. We use an identity matrix as the weighting matrix in Step 6.

Calibration and Estimation Results: We calibrate parameters that either are hard to estimate or which we believe there are good grounds for parametrizing using outside information rather than estimating. The vector of parameters that we calibrate is
$\Theta_1 = \left(\overline{R}, \xi, \mu, \overline{u}, \overline{\eta}, \kappa, \tau, \delta(1), \delta''(1), \gamma, \phi, \delta_R, \sigma_R^2\right)$. The parameters are calibrated to a monthly frequency and are summarized in Table 3.

We set steady-state gross inflation equal to one. The steady-state real rate, $\overline{R}$, is calibrated to 4 percent annual net return, $\overline{R} = 1.04^{1/12}$. We set the degree of risk aversion to $\mu = 2$, a standard value in the literature. Consumption is assumed to fall by 15 percent of the steady-state wage upon job loss and we calibrate accordingly $\xi = 0.85\overline{w}$. This value is a compromise between the estimates of Hurd and Rohwedder (2016) and Chodorow-Reich and Karabarbounis (2016) who find that consumption drops by 12 percent and 20 percent, respectively, upon job loss.

Next we assume that the steady-state unemployment rate equals 6 percent, which is close to the U.S. post-war average unemployment rate, and that the monthly job finding rate, η, is equal to 34 percent. The job finding rate implies an expected unemployment duration of around 13.5 weeks, the average duration in US post WWII data (excluding the Great Recession). In combination, these two parameters imply that the monthly job separation rate, ω, equals 3.3 percent. Next, we assume that the vacancy cost parameter, κ, is consistent with an average hiring cost of 4.5 percent of the steady-state wage.

Given these values, the agents' intertemporal discount factor follows as:

$$\beta = \frac{1}{\overline{R}\left(1 + \omega\left(1 - \overline{\eta}\right)\left(\left(\frac{\xi}{\overline{w}}\right)^{-\mu} - 1\right)\right)}$$

which gives us a value of $\beta = 0.9885$. At the annual frequency our calibration implies $\beta^{12} = 0.87$, a 13 percent annual real interest under complete markets. The low value of β derives from the precautionary savings motive which requires impatience on the part of households when targeting a low real interest rate.

The elasticity of the matching function with respect to unemployment, α, is set to 60 percent and we assume that the elasticity of output to employment is 65 percent. $\delta(1)$ is calibrated to match a capital-output ratio of 25 at the monthly frequency, which implies that $\delta(1) = 0.0024$. $\delta'(1)$ is normalized so that steady-state capacity utilization equals 1 and $\delta''(1)$ is set equal to 1 as well. We set the variance of the monetary policy shocks to $\sigma_R^2 = 0.001^2$ using the variance of the Romer and Romer monetary policy shocks series from the data.[22]

We set the elasticity of substitution between intermediate goods equal to 8 which implies a 12 percent mark-up in the steady-state. The value of ϕ determines the degree of nominal rigidities. One can relate this to the average price contract length by exploiting the relationship between the log-linearized NK Phillips curve in the Calvo model and the one implied by the Rotemberg model assumed in the current paper. In particular, the slope of the Phillips with respect to real marginal costs is equal to γ/ϕ, while the corresponding value in the Calvo model is $(1-\varpi)(1-\varpi\beta)/\varpi$ where $1/(1-\varpi)$ is the average contract length. We use this relationship to calibrate ϕ so that it corresponds to an average contract length of 6 months, a moderate amount of nominal rigidity.[23] We set also the coefficient on the persistence of interest rates on the Taylor rule equal to 0.5.

The vector of parameters that we estimate is $\Theta_2 = (\chi, \delta_\pi, \delta_\theta, \rho_A, \sigma_T, \sigma_S, \sigma_P, \rho_{CI}, \vartheta_1, \vartheta_2, \sigma_C)$. We scale σ_T and σ_S by σ_P, therefore estimate the ratio of the standard deviations of the transitory productivity shock and the noise shock to the standard deviation of the innovation to the persistent component of TFP. Figure 14 illustrates the simulated impulse response functions of the model given $\widehat{\Theta}_2$ together with their empirical counterparts. We match very well the impulse responses of consumer confidence, output and unemployment although the output response in the simulated data is slightly less elastic than in the data. The simulated matched responses also display a small increase in inflation and a drop in the nominal interest rate as in the actual U.S. data.

Table 4, column 1, contains the point estimates of $\widehat{\Theta}_2$ and also the implied endogenous earnings risk wedge Ψ. A key parameter is χ which determines the elasticity of the real wage to the job finding rate. High values of this parameter may imply that the endogenous earning risk wedge is procyclical which induces stabilization, while low values of χ more likely indicate a countercyclical risk wedge which leads to amplification. We find a $\widehat{\chi}$, of just above 2 percent. Thus, when the labor market improves, the real wage goes up but only to a small extent. Given this estimate (and the calibration of Θ_1), we find that the endogenous earnings risk wedge is $\widehat{\Psi} = 0.0034 > 0$ indicating that risk is countercyclical. This suggests amplification of shocks to the economy as we will look further into below.

Next, as far as monetary policy is concerned we find that $\widehat{\delta}_\pi = 1.166$ while $\widehat{\delta}_\theta = 0.00012$. The

[22]Given that our estimation targets the impulse responses, we can identify only the relative variances of the shocks. Hence, the calibration of σ_R^2 simply serves as an anchor.

[23]The implied value of the price adjustment parameter is $\phi = 227$.

latter may seem small but tightness varies a lot over the business cycle. The estimated value of δ_π is not far from estimates in complete markets models and indicates that real rates decline in response to increases in inflation although this may happen gradually due to the interest rate smoothing. $\widehat{\delta}_\theta$ implies that the central bank cuts the interest rate when labor market slackness increases.

Next, ρ_A, the AR(1) parameter of the persistent component of technology, is estimated to be just below 92 percent at the monthly frequency while the standard deviation of the innovation to the persistent component is estimated to be 0.088 percent per month. We find that the transitory shock is more volatile than the persistent shock, $\widehat{\sigma_T/\sigma_P} = 1.144$, while $\widehat{\sigma_S/\sigma_P} = 1.318$ indicating that a substantial amount of the variation in the signal is due to noise. We will look at the impact of this below.

The estimates of the parameters of the model equivalent of consumer confidence, equations (29)-(30), indicate high persistence, $\widehat{\rho}_{CI}$, and that most of the innovations in this variable derive from revisions in the estimates of the persistent component of productivity since $\widehat{\vartheta}_2 > \widehat{\vartheta}_1$. The high persistence of consumer confidence and the high value of $\widehat{\vartheta}_2$ in combination indicate that noise shocks can have a persistent impact on consumer confidence as we estimate in the data.

Implications

We now explore some properties of the estimated model. Figure 15 illustrates the expectations that agents form about the persistent component of technology conditional on the innovations to the four structural shocks (circled lines). Of primary interest for our purposes are the impact of actual persistent technology shocks and of noise shocks. Although the actual process for persistent technology shocks is an AR(1) process with a high root, agents perceive a hump-shaped response of $A^p_{s,s}$ as there initially is uncertainty about whether the increase in total productivity derives from persistent or temporary shocks. Eventually as productivity remains high, after 5-6 months, agents realize that the increase in the observed indicator of productivity derives from a persistent shock. Agents also initially confuse a noise shock with an increase in the persistent component of technology. This confusion persists for around 4-5 months before eventually dissipating. The reason for this is the high estimated value for the variance of the transitory technology shock which implies that the agents take time to be convinced that the signals that they receive about the persistent technology shocks derive from noise rather than an actual persistent technology shock. It is this confusion that implies that noise shocks can have real effects.

Figure 16 illustrates the response of the economy to a negative noise shock. The negative noise shock sets off a decline in agents' expectations about the persistent component of technology. The decline in consumer sentiments induced by the noise shock triggers a recession in the economy that lasts approximately a year. Since we estimate that $\Psi > 0$, the endogenous earning risk wedge is countercyclical and the model incorporates an amplification mechanism through precautionary savings. In particular, in response to the negative noise shock, the job finding rate declines. The drop in the job finding rate is a consequence of firms' cutting back on vacancy postings and by an increase in unemployment. This happens both because agents believe that future productivity will decline (due to the noise signal) and because of the contraction of goods demand induced by employed agents increasing their precautionary savings. Due to the perceived low productivity and falling employment, firms also reduce the capacity utilization rate. Hence, output declines and firms cut down on investment in real capital (not shown in the picture). In summary, the model introduces a substantial propagation of the noise shocks through both expectations and through behavioral responses.

The inflation and nominal rate responses to the noise shock are very small. Given the negative effects of the shock one would expect that the model would generate deflation, yet, the noise shock is a perceived shock to the supply side of the economy that increases marginal costs and, hence prices. In equilibrium these two effects cancel out. The interest rate response follows mostly the inflation one given the estimated values of the monetary policy rule.

The role of countercyclical risk

The countercyclical risk is crucial for the amplification mechanism which allows us to account for the substantial rise in unemployment that we estimate in the data in response to the decline in consumer sentiments. To illustrate this more clearly, Figure 17 contrasts the responses of the different variables in the benchmark model with the response in a version of the model where we increase the real wage elasticity to 0.178 in order to induce a procyclical endogenous earnings risk wedge which is exactly of the same absolute size as in the estimated case (circled lines, $\Psi = -0.0034$). When we introduce procyclical endogenous risk, the response of all real variables are negligible because the incentive to increase the savings rate for precautionary reasons is neutralized. That is, in the absence of countercyclical risk, the predictions of the model coincide with the predictions of the model suggested by Barsky and Sims (2012), for which noise does not matter for cyclical fluctuations.

The countercyclical risk channel therefore introduces a complementarity which amplifies the real effects of noise shocks in a similar spirit to Angeletos *et al.* (2018). In the latter authors' framework, the complementarity relates to heterogeneous beliefs, while in our framework the complementarity relates to uninsurable idiosyncratic earnings risk and the ramifications thereof. On the other hand, the model with countercyclical risk implies more monetary stability because the larger demand contraction counteracts producers perception of higher marginal costs. In the data, we find real instability relative to nominal variables in response to sentiment shocks and the model with countercyclical risk is consistent with this.

The role of monetary policy

We can use our theoretical model to run policy experiments. According to our estimates, monetary policy reacts little to labor market tightness, the estimated coefficient of $\delta_\theta = 0.00012$. In Figure 18, we increase the value of $\delta_\theta = 0.005$. Ravn and Sterk (2018) show that the amplification of shocks depends on the difference between $\rho\beta\overline{R}\Psi$ and $\delta_\theta / (1-\alpha)$ and this difference changes from -0.0031 to 0.0019 when increasing δ_θ so that the more aggressive monetary policy response neutralizes the amplification mechanism. The results confirm this. In particular, we find that when monetary policy would react more aggressively to labor market tightness (diamond lines), it stabilizes the economy substantially because any rise in unemployment is accommodated by lower interest rates which stabilizes expectations and mutes the amplification mechanism. However, such accommodation of variations in labor market tightness comes at the cost of higher volatility in inflation, and, hence, the nominal interest rate. In other words, sentimental shocks in our framework are not subject to the divine coincidence as other demand shocks are. In order for the central bank to correct for deviations of unemployment it needs to trade-off higher inflation in the short run. This is an important result, given the significance of sentiment shocks to explain business cycle fluctuations in the data. By reacting to the labor market conditions the monetary policy decreases the strength of the negative effect the shock induces on precautionary savings and breaks the vicious circle that propagates sentiment shocks in the economy. However, reducing the demand effects of the shock cannot help constrain the supply effects arising from a perceived increase in marginal costs from the part of producers and in equilibrium this implies a rise in inflation.

The role of noise

In the model economy, noise shocks perturb the signals that agents receive about the persistent component of productivity. Holding other parameters constant, a higher variance of noise shocks makes the signal less informative and lowers the agents' response to the signal. We show this in Figure 19 where we plot the impulse responses in the model economy to noise shocks for the benchmark estimation and for a case in which we double σ_S. When the variance of the noise shock increases, the economy's response to these shocks becomes very muted (and in the limit, agents will simply update $A^P_{s-1,s}$ with their information on A_s when forming $A^P_{s,s}$).

In this light, it is interesting to consider the evidence on the instrument relevance that we discussed in the empirical section. Recall that while we find fatalities in mass shootings to be a strong instrument in our benchmark sample, the increase in the severity and number of mass shootings in the last three years of the sample implies that the instrument losses relevance for the ICE when we include data up to the end of November 2018 and falls quite a lot when extending up to end of 2015.

In Figure 20 we report outcomes of the first stage weak instrument tests implemented on simulated model data when we vary the variance of the noise shock, σ_S^2, holding constant all other parameters. In particular, we estimate the 5 variable VAR that we use for the simulation estimator by simulating the model holding all parameters but σ_S constant and compute the first-stage F-statistic (averaging over 200 simulations for each value) for the hypothesis that the noise shock has no explanatory power for (the model equivalent of) consumer confidence.

The relationship between the variance of the noise shock and the first stage F-test follows an inverse U-shape. When the noise shock has very low variance, it is a weak instrument despite the signal being very precise (and therefore having informational content for agents' forecasts of the persistent component of productivity). Recall from above (c.f., equation (29)) that the model-equivalent of consumer confidence depends positive on agents' revisions of the persistent component of technology, on the difference between actual and forecasted productivity, and that there are transitory measurement errors. The revisions of the forecast for the persistent component of productivity are obtained in response to noise shocks but these contribute very little relative to innovations to the persistent and transitory productivity shocks. Therefore, were noise shocks irrelevant (due to having very low variance), they will also be a poor instrument for consumer confidence.

As the variance of the noise shock increases, these shocks gain relevance and there is a wide range of values of σ_S^2 for which they imply F-values in the range required for strong instrument. In this range, agents revise their estimates of the persistent component of productivity in response to these shocks which influence consumer confidence and make the noise shocks relevant in an IV sense. However, as the noise shock becomes ever more volatile, it loses relevance. This derives from agents' information processing. When σ_S^2 is very large, the signal is very imprecise and agents will tend to ignore it. Hence, in this case again, most of the variation in consumer confidence derives from "fundamental" shocks (and measurement error) leaving the noise shock having little impact on (29).

Thus, the model helps understanding why the significant rise in the intensity and frequency of mass shootings in the U.S. at the end of the sample period invalidates the use of this instrument.

4.B The Impact of Technology Shocks

A byproduct of our analysis concerns the estimates of structural parameters that also influence how the economy responds to "fundamental" shocks, and it is interesting also to investigate the results in this dimension. In Figure 21 we illustrate the impact of persistent technology shocks in the incomplete markets model with imperfect information and again compare with the case in which we increase the real wage elasticity to 0.178 (which implies a procyclical earning risk wedge, i.e., $\Psi = -0.0034$).

Three key results stand out. First, although the true technology shock is autoregressive, the impact of technology shocks follow a hump-shaped pattern when the endogenous earning risk is countercyclical. This is explained by labor market matching, which means that employment increases gradually over time, in combination with imperfect information through which it takes time before agents in the economy become convinced about the source of fluctuations in the economy. This shows that habit formation and capital (or investment) adjustment costs are not needed for generating partial adjustment-like responses to fundamental shocks. Interestingly, when real wages are more elastic, this partial adjustment dynamics is no longer present in output.

Secondly, the model with a countercyclical risk wedge generates a substantial amount of amplification on output, consumption, and, especially labor market variables. When wages are very elastic, firms naturally hold back on employment adjustments which stabilizes the labor market but also aggregate consumption and, therefore, output. Instead, when the wage elasticity is small and the risk wedge is countercyclical, firms respond to the increase in productivity by posting more vacancies which increases the job finding rate. In response to this, employed workers perceive a drop in unemployment risk and increase goods demand. Through these sources, the impact of shocks is amplified substantially especially as far as labor market variables are concerned.

Third, the impact of technology shocks on inflation dynamics and nominal interest rates is very muted in the model with a countercyclical risk wedge relative to the economy with very elastic real wages. This derives from the fact that while higher productivity lowers marginal costs, in the countercyclical wedge model, it also stimulates consumption demand through not only standard wealth and intertemporal savings channels but also due to the drop in precautionary savings demand. Moreover, since the central bank responds to labor market tightness, the improvement in labor market conditions moderates the decline in the nominal interest rate.

5 Conclusion

The empirical role of consumer sentiment shocks as a driver of business cycle fluctuations remains debated in the literature, with findings hinging upon the identification assumptions used. In this paper we remain agnostic as to what sentiment shocks should look like and use an instrumental variable approach to identify exogenous movements in consumer confidence. Mass shootings in the U.S. are shown to significantly reduce consumer confidence expectations and, using these events as a natural experiment, we then show that exogenous drops in consumer confidence generate a persistent contraction in economic activity that affects substantially the labor market.

We have developed and estimated through indirect inference an incomplete markets general equilibrium model with heterogeneous agents with search and matching frictions in the labor market and nominal rigidities in the goods' markets. We have shown that sentiment shocks, which capture changes in beliefs about future productivity that are orthogonal to fundamentals induce cyclical fluctuations when agents adjust consumption in response to changes in the expected job finding rate because of precautionary savings. We show, in particular, that countercyclical endogenous income risk amplifies the impact of sentiment shocks and that monetary policy can smooth fluctuations due to sentiments by reacting to labor market conditions at the cost of higher inflation volatility.

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6 Tables and Figures

Table 1: **F-Test Values for Instrument Relevance Tests**

Part A: Benchmark VAR			
Sample	Proxy	F-test value (F^{HOM})	F-test value (F^{MOP})
1965:1-2007:8	MassFat_7	11.3	17.6
1965:1-2015:12	MassFat_7	11.8	6.3
1965:1-2018:11	MassFat_7	5.4	2.4
1965:1-2007:8	MassFat_3	8.9	7.3
Part B: Alternative VAR-specifications, 1965:1-2007:8			
Confidence	Observables	F-fest value (F^{HOM})	F-test value (F^{MOP})
ICC	Benchmark	3.2	3.8
ICS	Benchmark	9.7	12.7
BUS5	Benchmark	5.3	5.6
BUS12	Benchmark	9.0	19.0
ICE	CPI inflation	10.1	13.4
ICE	no SP500	9.4	17.2
ICE	no U12	9.2	12.9
ICE	no SP500, U12	7.3	12.6

Note: The table records the outcomes of the first-stage F-statistics for the null hypothesis that the instrument has no explanatory power for consumer confidence. stands for the F-test statistics for the null of standard conditional homoscedasticity (and no serial correlation), and for the Montiel-Olea and Pflueger (2013) HAR-robust F-statistics.

Table 2: **Forecast Error Variance Decomposition**

	Forecast horizon (months)					
Variable	1	3	6	12	48	120
Index of consumer expectations	75	70	59	49	36	28
Unemployment rate	26	34	40	44	25	20
Vacancies	39	40	37	34	17	13
Labor market tightness	20	20	19	18	16	15
hours worked per worker	3	15	19	16	7	8
Capacity utilization	11	18	21	19	7	7
Industrial production	12	19	25	25	14	13
Consumption of non-durables	16	28	31	37	38	32
Consumption of durables	8	21	23	18	20	15
Inflation rate	25	20	14	11	4	4
Federal funds rate	3	9	17	20	18	15
Stock prices	3	4	4	5	12	13
Uncertainty	9	7	6	4	3	4

Note: The table records the point estimates of the percent of the total forecast error variance in different variables accounted for by identified sentiment shock at various forecast horizons. The VAR includes 18 lags and is estimated for the sample period 1965:1 - 2007:8.

Table 3: **Calibration of Θ_1**

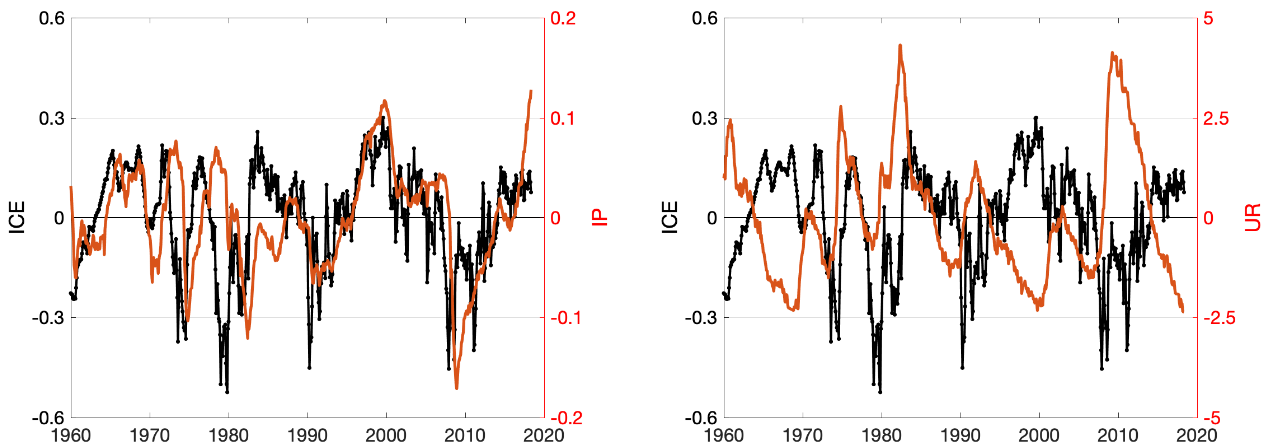
Parameter	Meaning	Value
$\overline{\mathbf{u}}$	steady state unemployment rate	6 percent
$\overline{\eta}$	steady state job finding rate	34 percent
α	matching function parameter	0.6
$(\kappa/\overline{\mathbf{q}})\,/\,(3\overline{\mathbf{w}})$	steady state hiring cost	4.5 percent
ζ	price contract length	6 months
γ	elasticity of substitution between varieties	8
τ	output elasticity to capital	0.35
$\xi_{\delta,z}$	elasticity of depreciation rate to capacity utilization	1
δ	depreciation rate (annually)	7.1 percent
$\overline{\mathbf{R}}/\overline{\Pi}$	steady state gross real interest rate rate	$1.04^{1/12}$
$\overline{\Pi}$	steady state gross inflation rate	1
δ_R	interest rate smoothing	0.8
σ_m	standard deviation of monetary policy shock	0.1 percent
μ	Coefficient of relative risk aversion	2
$(c_e - c_u)\,/c_e$	steady state consumption drop upon job loss	15 percent
Implied parameters		
ω	Monthly job separation rate	0.0329
δ	Monthly depreciation rate	0.0024

Table 4: Parameter Estimates

Table 5: Estimated values of Θ_2

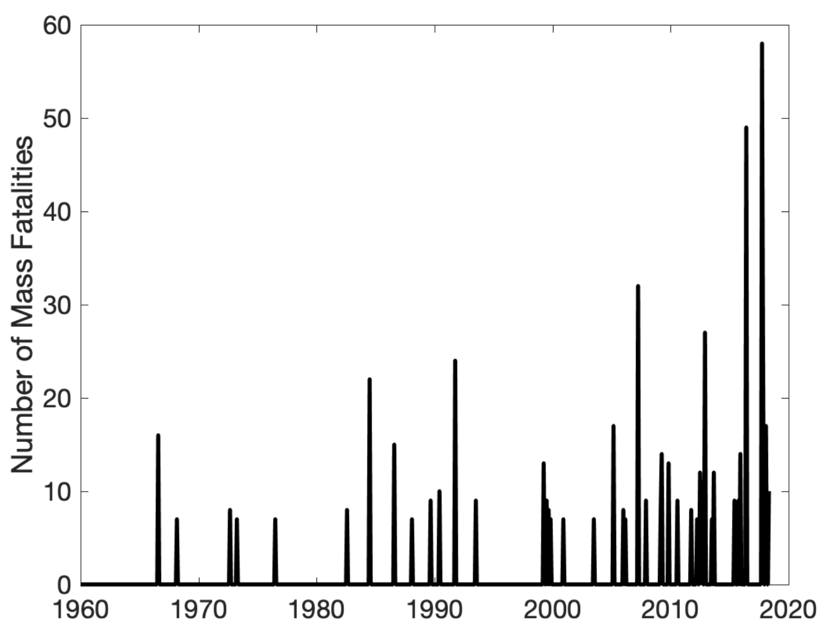
	Parameter Estimates	
Parameter	Description	Estimated values
χ	elasticity of real wage to job finding rate	0.0211
ρ_A	persistence of technology shock	0.9165
σ_P	model-based std. dev confidence shock	0.00088
σ_T/σ_P	std. dev. of transitory shock	1.144
σ_S/σ_P	std. dev. of noise shock	1.318
δ_π	inflation coefficient on Taylor rule	1.166
δ_θ	reaction of monetary policy to tightness	0.0001
ρ_{CI}	persistence model-based confidence measure	0.923
ϑ_1	Kalman filter parameter model-based confidence measure	3.4198
ϑ_2	Kalman filter parameter model-based confidence measure	28.40
σ_C	std. dev. confidence shock	.0005
σ_m	std. dev. of measurement error for noise	0.0001
Implied parameters		
Ψ	Implied risk wedge	0.0034

Figure 1: Consumer Confidence vs. Industrial Production and Unemployment



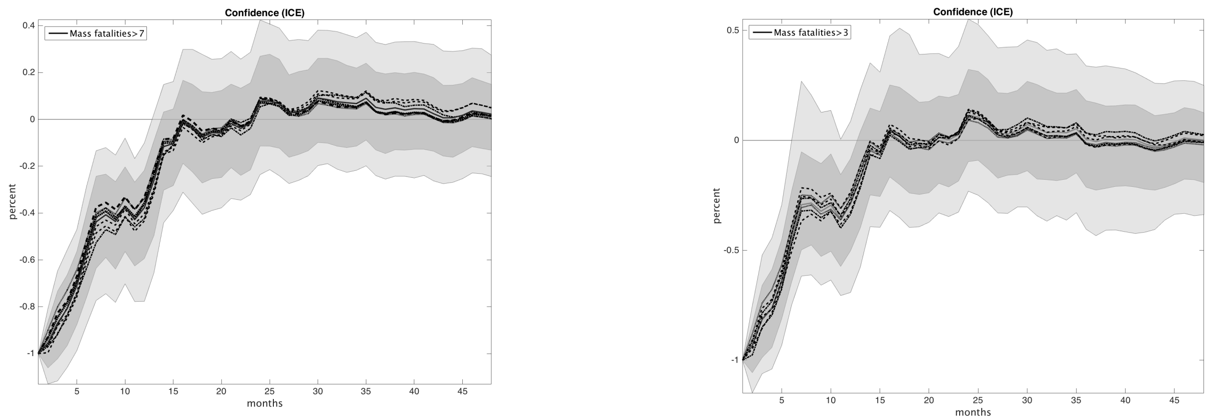
Note: The graph presents time series of detrended ICE against industrial production (left panel) and unemployment (right panel) from 1965:1 to 2018:11. All series have been detrended with 4th order time polynomials.

Figure 2: Timeline of Mass Shootings and Fatalities



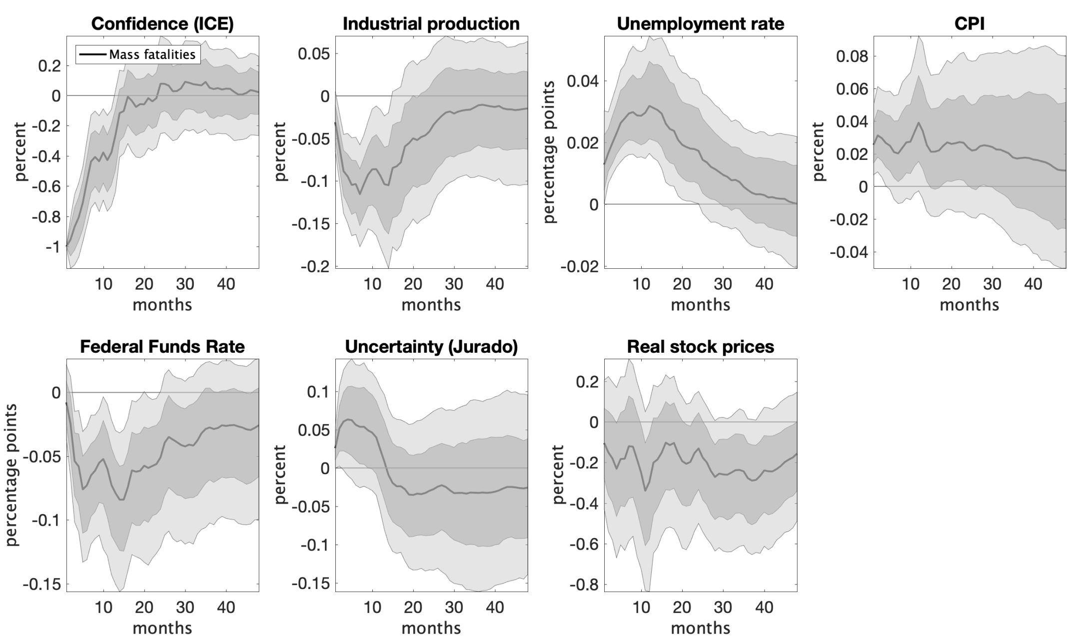
Note: The graph presents the timeline of mass fatalities with more than 7 victims between 1965:1 to 2018:11.

Figure 3: Confidence Response to the IV



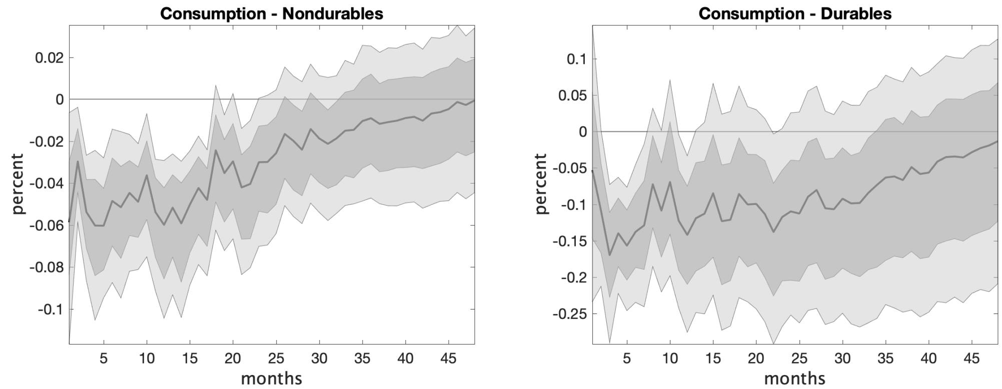
Note: The continuous line depicts point estimates of the impact of the identified sentiment shock on the ICE. Dark grey and light grey areas represent 68 and 90 percent confidence bands based on the parametric bootstrap, respectively, while discontinuous lines depict point estimates of the impulse response functions from specifications in which we exclude each of the mass shootings with more than 10 fatalities one-by-one. The sample period is 1965:1-2007:8.

Figure 4: Consumer Sentiment Shock IRF - Benchmark



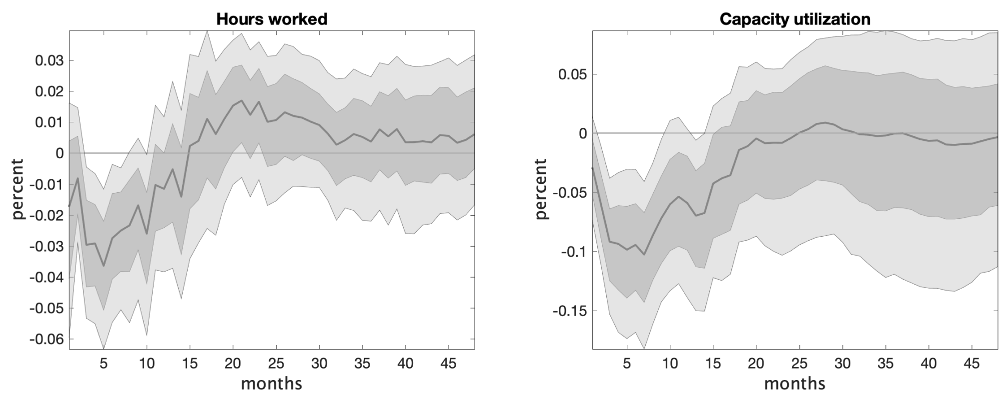
Note: The graph plots impulse response functions to a sentiment shock. The continuous line depicts point estimates of the impact of the identified sentiment shock on the different variables in the VAR. Dark grey and light grey areas represent 68 and 90 percent confidence bands based on the parametric bootstrap. The sample period is 1965:1-2007:8.

Figure 5: Consumer Sentiment Shock IRF - Nondurables and Durables Consumption



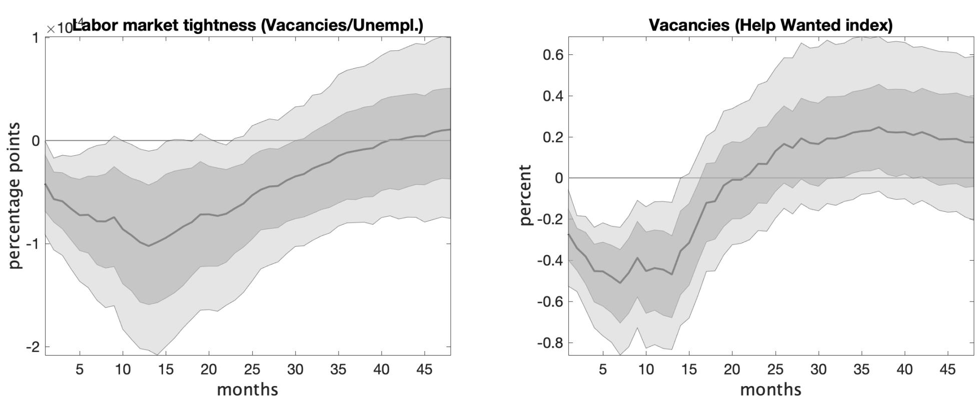
Note: The graph plots impulse response functions to a sentiment shock. The continuous line depicts point estimates of the impact of the identified sentiment shock on consumption of non-durables (left) and durables (right). Dark grey and light grey areas represent 68 and 90 percent confidence bands based on the parametric bootstrap. The sample period is 1965:1-2007:8.

Figure 6: Consumer Sentiment Shock IRF - Hours Worked and Capacity Utilization



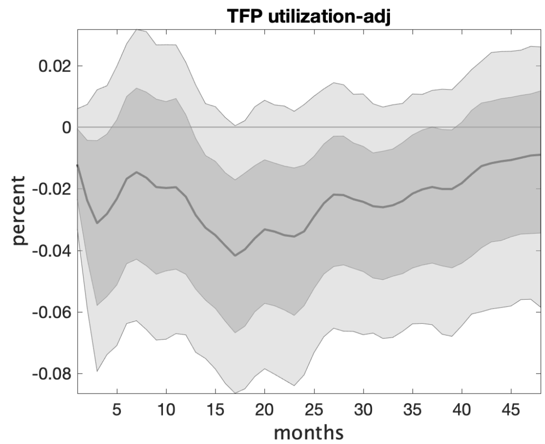
Note: The graph plots impulse response functions to a sentiment shock. The continuous line depicts point estimates of the impact of the identified sentiment shock on hours worked (left) and capacity utilization (right). Dark grey and light grey areas represent 68 and 90 percent confidence bands based on the parametric bootstrap. The sample period is 1965:1-2007:8.

Figure 7: Consumer Sentiment Shock IRF - Labor Market Variables



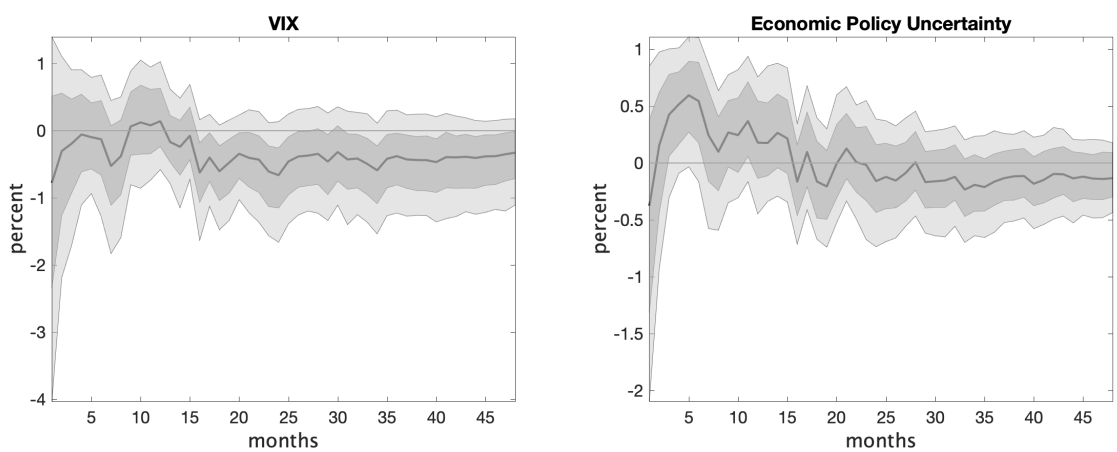
Note: The graph plots impulse response functions to a sentiment shock. The continuous line depicts point estimates of the impact of the identified sentiment shock on labor market tightness (left) and vacancies (right). Dark grey and light grey areas represent 68 and 90 percent confidence bands based on the parametric bootstrap. The sample period is 1965:1-2007:8.

Figure 8: Consumer Sentiment Shock IRF - Total Factor Productivity



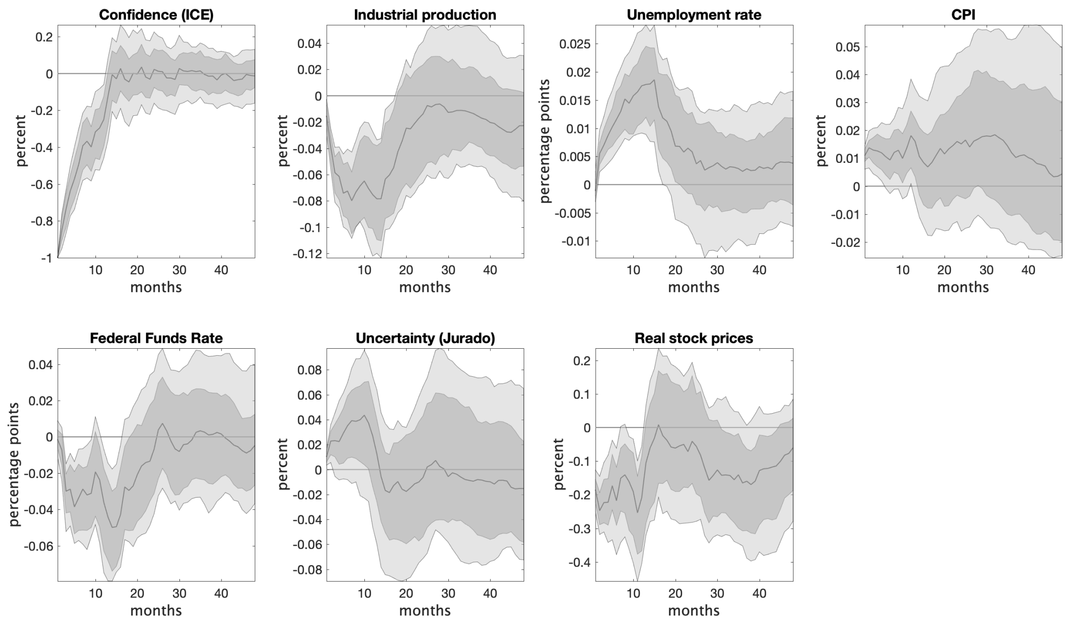
Note: The graph plots impulse response functions of utilization adjusted TFP to a sentiment shock. The continuous line depicts point estimates and dark grey and light grey areas represent 68 and 90 percent confidence bands based on the parametric bootstrap. The sample period is 1965:1-2007:8.

Figure 9: Consumer Sentiment Shock IRF - VIX and EPU



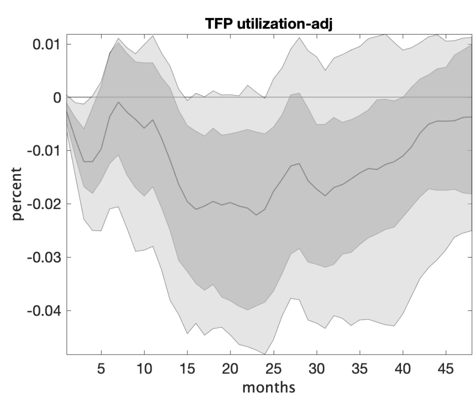
Note: The graph plots impulse response functions of uncertainty measures to a sentiment shock. The left panel presents responses of the VIX and the right panel responses of the Economic Policy Uncertainty index. The continuous line depicts point estimates and dark grey and light grey areas represent 68 and 90 percent confidence bands based on the parametric bootstrap. The sample period is 1965:1-2007:8.

Figure 10: Cholesky SVAR - Baseline Variable Responses



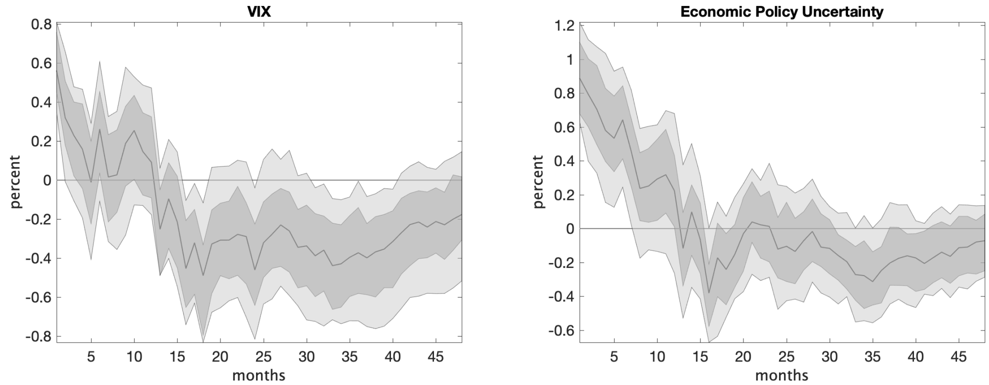
Note: The graph plots impulse response functions to a sentiment shock identified using Cholesky zero short-run restrictions as an alternative identification strategy. The continuous line depicts point estimates of the impact of the identified sentiment shock on the different variables in the VAR. Dark grey and light grey areas represent 68 and 90 percent confidence bands based on botstrap. The sample period is 1965:1-2007:8.

Figure 11: Cholesky SVAR - TFP Response



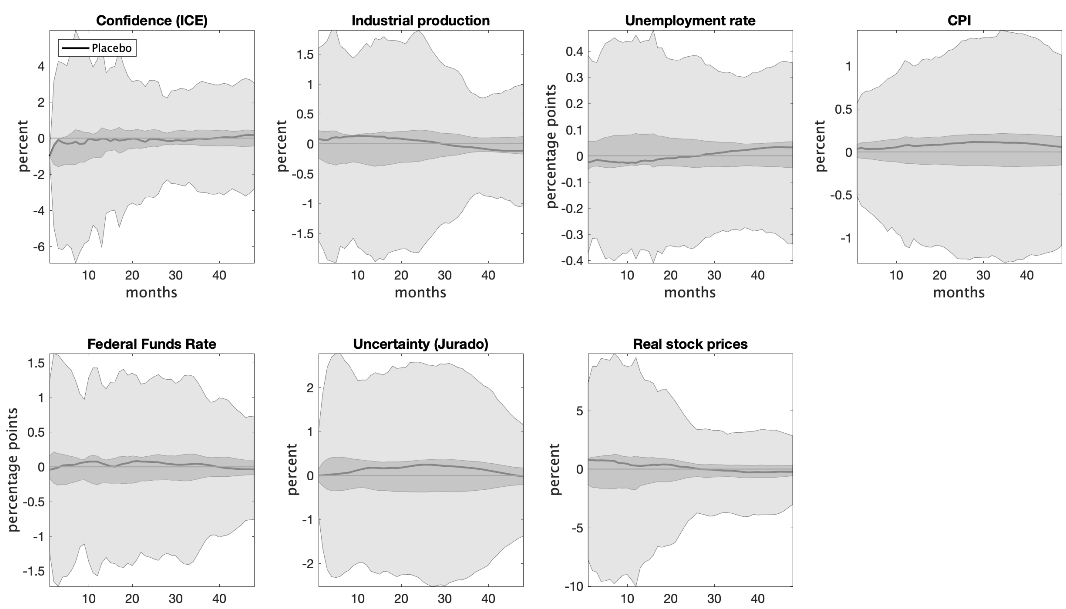
Note: The graph plots the impulse response function of utilization-adjusted TFP to a sentiment shock identified using Cholesky zero short-run restrictions as an alternative identification strategy. The continuous line depicts point estimates of the impact of the identified sentiment shock on the different variables in the VAR. Dark grey and light grey areas represent 68 and 90 percent confidence bands based on bootstrap. The sample period is 1965:1-2007:8.

Figure 12: Cholesky SVAR - VIX and EPU Responses



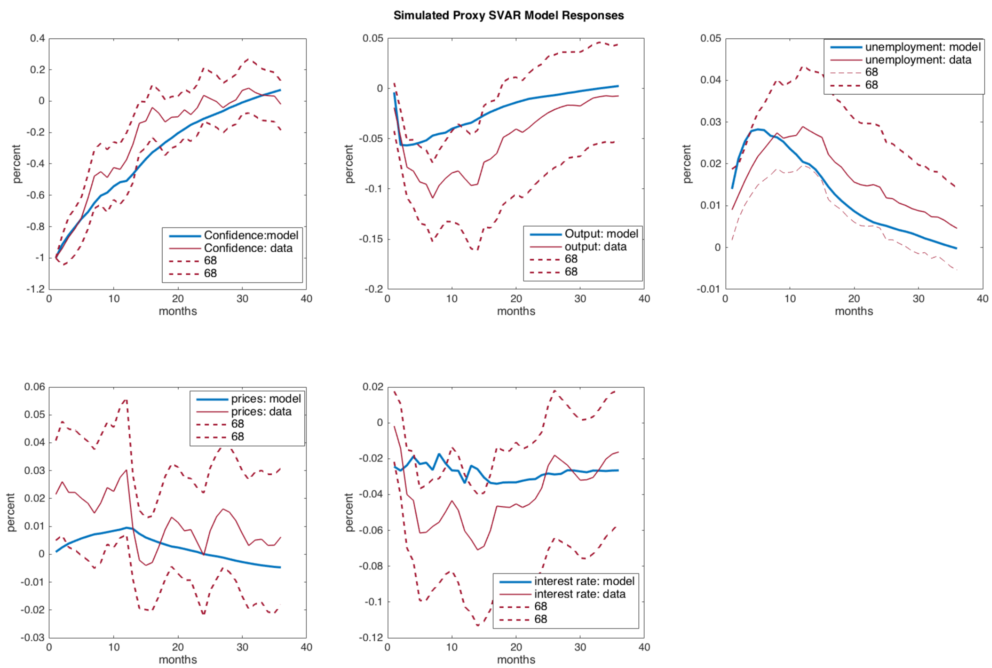
Note: The graph plots impulse response functions to a sentiment shock identified using Cholesky zero short-run restrictions as an alternative identification strategy. The left panel presents responses of the VIX and the right panel responses of the Economic Policy Uncertainty index. The continuous line depicts point estimates of the impact of the identified sentiment shock on the different variables in the VAR. Dark grey and light grey areas represent 68 and 90 percent confidence bands based on bootstrap. The sample period is 1965:1-2007:8.

Figure 13: Proxy SVAR: Placebo with Reshuffled Shootings



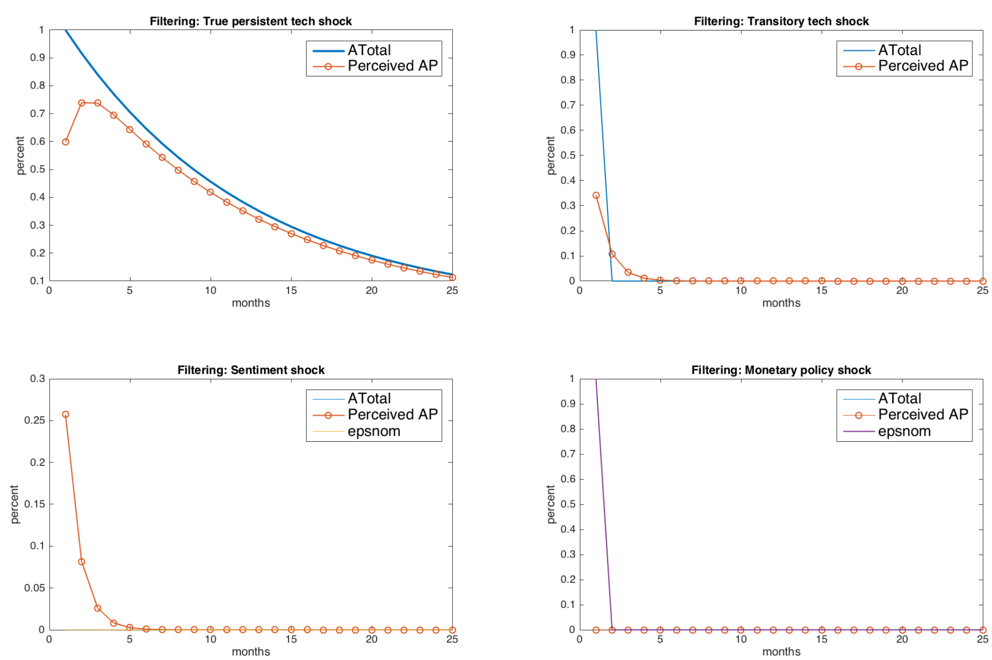
Note: The graph plots impulse response functions to a shock in a proxy-SVAR in which we replace the proxy variable with randomly reshuffled mass shooting fatalities. The reordering is drawn from a uniform averaged over 10,000 replications. The continuous line depicts point estimates of the impact of the identified sentiment shock on the different variables in the VAR. Dark grey and light grey areas represent 68 and 90 percent confidence bands based on the parametric bootstrap. The sample period is 1965:1-2007:8.

Figure 14: Simulated Responses to Sentiment Shock From Estimated Model



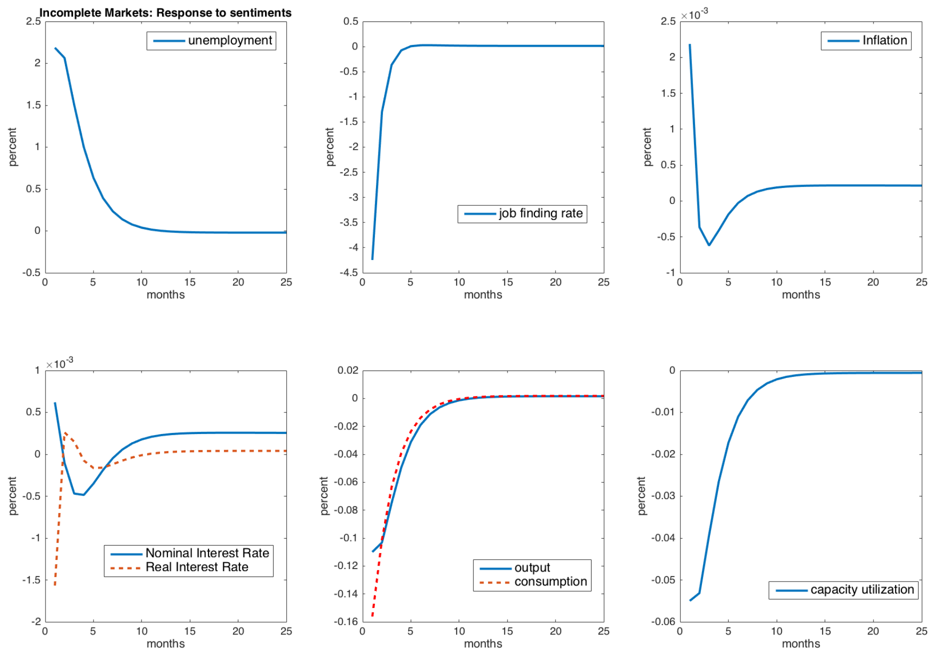
Note: The graph plots impulse response functions to a sentiment shock. The continuous red line depicts point estimates of the impact of the identified sentiment shock on the different variables in the VAR. Dotted red lines represent 90 percent confidence bands. The sample period is 1965:1-2007:8. The continuous blue lines depicts point estimates of the impulse responses to a sentiment shock identified using the simulated data.

Figure 15: Theoretical Impulse Responses Expectation Formation



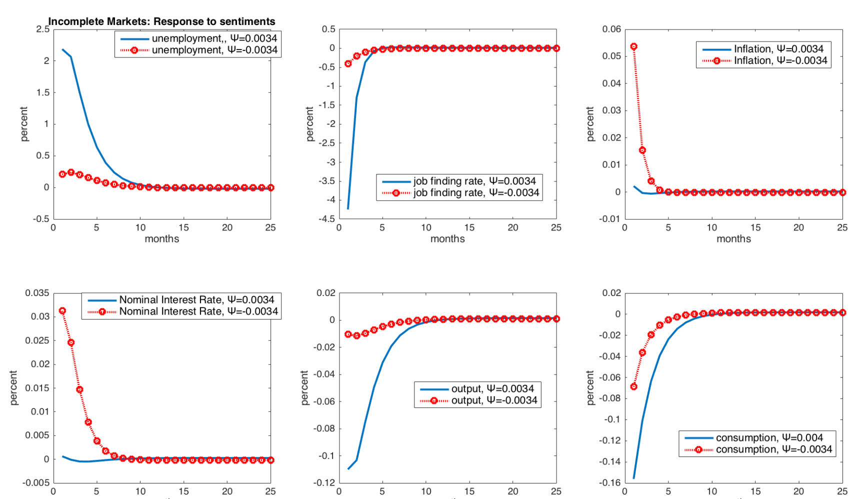
Note: The figure illustrates the expectations that agents form about the persistent component of technology conditional on the innovations to the four structural shocks (circled lines) in the theoretical model.

Figure 16: Theoretical Impulse Responses to Sentiment Shock



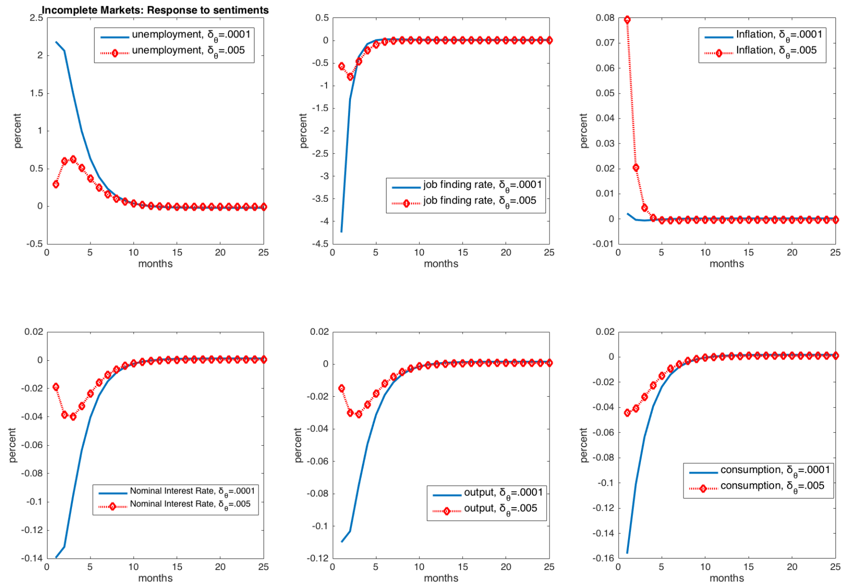
Note: The figure illustrates the theoretical impulse responses to a negative sentiment shock.

Figure 17: Theoretical Impulse Responses: The Impact of Countercyclical Risk



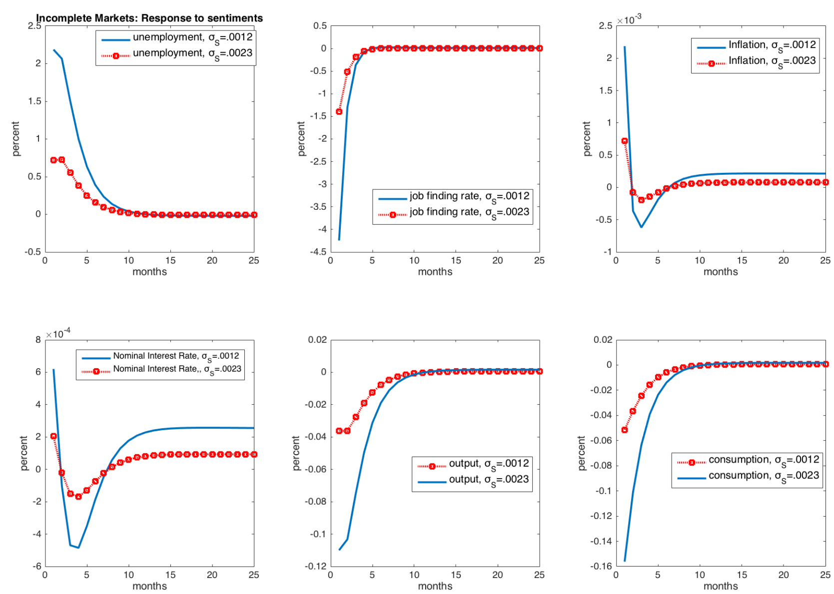
Note: The figure illustrates the theoretical impulse responses to a negative sentiment shock in the baseline model (continuous lines, $\Psi = 0.0034$) and in the model in which we set $\chi = 0.187$ in order to generate a procyclical endogenous earnings risk wedge which is exactly of the same absolute size as in estimated case (Ψ = -0.0034).

Figure 18: Theoretical Impulse Responses: The Role of Monetary Policy



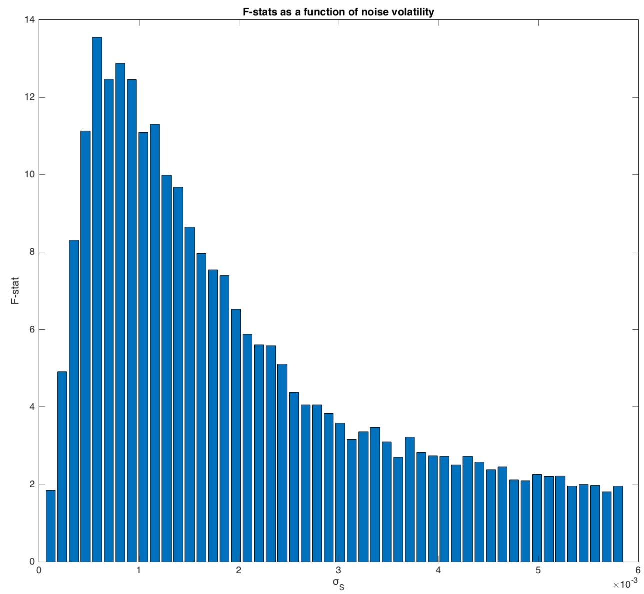
Note: The figure illustrates the theoretical impulse responses to a negative sentiment shock in the baseline model (continuous lines, $\delta_\theta = 0.0001$) and in the model in which we set $\delta_\theta = 0.005$, allowing monetary policy to react to the labor market conditions (diamond lines).

Figure 19: Theoretical Impulse Responses: The Role of Noise



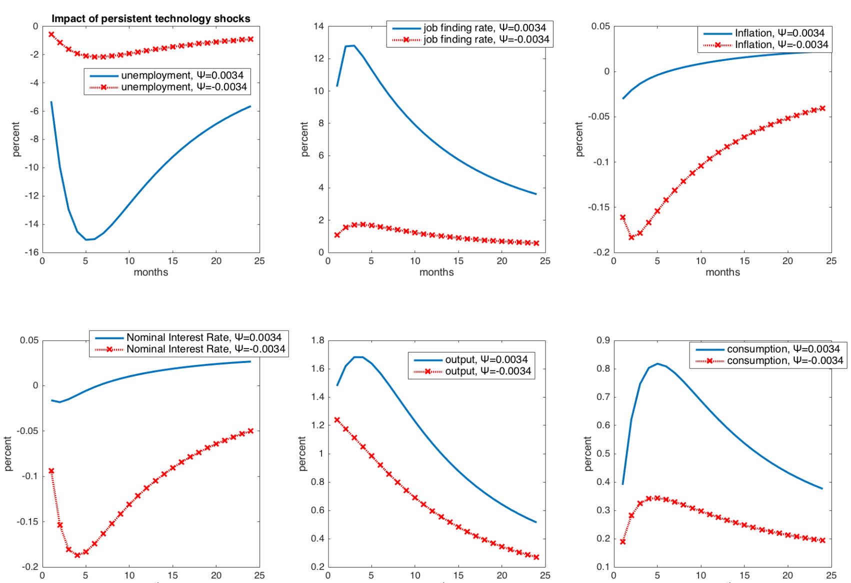
Note: The figure illustrates the theoretical impulse responses to a negative sentiment shock in the baseline model (continuous lines, $\sigma_S = 0.0012$) and in the model in which we double the variance of the sentiment shock $\sigma_S = 0.0023$ (squared lines).

Figure 20: Variance of Noise Shock and First-Stage F-statistic



Note: The graph plots first stage weak instrument tests implemented on simulated model data when we vary the variance of the noise shock, σ_S^2, holding constant all other parameters for the hypothesis that the noise shock has no explanatory power for (the model equivalent of) consumer confidence.

Figure 21: Theoretical Impulse Responses to Persistent Technology Shock



Note: The figure illustrates the theoretical impulse responses to a positive persistent technology shock in the baseline model (continuous lines, $\Psi = 0.0034$) and in the model in which we set $\chi = 0.187$ in order to generate a procyclical endogenous earnings risk wedge which is exactly of the same absolute size as in estimated case (circled lines, $\Psi = 0.0034$).