Abstract

We use an IV framework to identify the dynamic causal effects of consumer sentiments on the aggregate U.S. economy. We suggest to instrument autonomous shocks to consumer sentiments with fatalities in mass shootings in the U.S. We demonstrate that mass fatalities is a strong instrument and find that an autonomous deterioration in consumer sentiments is recessionary, non-deflationary, and persistent. We also show a deterioration in consumer sentiments is accompanied by a monetary expansion. We then construct an heterogeneous agents’ new Keynesian model with search and matching frictions and estimate its structural parameters in order to match theoretical and empirical impulse responses to sentiment shocks. Sentiment shocks induce a supply-demand feedback mechanism. Countercyclical earnings’ risk amplifies their negative demand effects and the reaction of the central bank becomes crucial to determine which effect dominates in equilibrium.

Keywords: Consumer sentiments, mass shootings, dynamic causal estimates, monetary policy, incomplete markets, sticky prices, heterogenous agents, search and matching.

JEL: E32, E62
1 Introduction

A central topic in macroeconomics concerns the sources of fluctuations in the economy and their propagation mechanism. An extensive literature has provided empirical evidence on the impact of ‘identified’ shocks (e.g. see the recent comprehensive survey of Ramey, 2016). This literature has focused upon estimating ‘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. However, under a variety of conditions, the economy may also fluctuate over time in response to non-fundamental shocks, such as expectational errors or “animal spirits”. There is however, very little direct evidence on the impact of such shocks and how they propagate over time. This paper addresses this issue. We estimate the impact of autonomous changes in consumer sentiments and relate the results to economic theory. We show that a worsening in consumer sentiments has persistent recessionary effects on the economy.

The central challenge to estimating non-fundamental shocks is that they are non-observable. We tackle this problem by focusing on a specific source of non-fundamental shocks that trigger autonomous changes in consumer sentiments, by utilizing an instrumental variable approach for identification. To measure consumer sentiments, we draw on the University of Michigan Survey of Consumer Confidence which records consumers’ views about the current and future outlook for their own financial situation and for the aggregate U.S. economy. One can think of such survey evidence as reflecting the respondents’ views about current fundamentals, their views about future fundamentals, and autonomous changes in consumer sentiments.

But how does one tell apart a change in confidence sparked by agents receiving news about current or future fundamentals from an autonomous change in confidence that possibly impacts on future observables? We suggest to instrument autonomous changes in consumer sentiments with fatalities in mass shootings in the U.S. There is considerable evidence that mass shootings can impact individuals’ psychological well-being as measured by e.g. PTSD symptoms (Hughes et al., 2011) as well as subjective well-being (Clark and Stancanelli, 2017). Moreover, mass killings receive considerable national news coverage indicating that their incidence may impact on a broad cross-section of the population. Thus, to the extent that well-being is linked to consumers’ optimism about their own and the U.S. economy’s current and future outlook, it is ex-ante plausible that these events may be reflected in survey evidence on consumer confidence.

In order to examine this, we study data on fatalities in mass shootings drawn from a database
constructed by MotherJones (2017). We extend a database constructed by MotherJones\textsuperscript{1} of mass shootings defined as incidents with minimum four fatalities (excluding the perpetrator) carried out by a lone shooter in a public sphere. From 1960 to mid-2017, there were no less than 754 fatalities deriving from 98 separate events with the most lethal ones being the 2016 Orlando nightclub massacre (49 fatalities) and the Virginia Tech massacre in April 2007 (32 fatalities).

Although many of these events incur a tragic loss of human life and have spurred discussions about gun laws, they occur on a sufficiently regular basis that each individual event is unlikely to have induced direct economic costs. Furthermore, we demonstrate that the timing of these events appears unrelated to the state of the economy. This is important because we will use mass shootings to instrument for autonomous changes in consumer confidence. This identification strategy relies on exogeneity of mass shootings and on the exclusion restriction, that mass shootings do not directly impact on the observables.

Technically, to derive estimates of the dynamic causal effects of consumer sentiments, we use the proxy SVAR framework of Mertens and Ravn (2013). Our benchmark VAR consists of the index of consumer expectations obtained from the University of Michigan survey, industrial production, civilian unemployment, the consumer price level, and the short term nominal interest rate, with monthly data for the 1960-2017 sample period. We show that fatalities in mass shootings is a strong instrument for shocks to consumer confidence when including the other variables in the VAR as covariates. In the aftermath of a mass shooting, we find that consumer confidence declines persistently. Furthermore, the identified consumer sentiment shocks are shown to significantly impact the US economy, whereby a deterioration in consumer sentiments induces a persistent increase in unemployment and a reduction in industrial production.

Augmenting the VAR with additional data series (one at a time) sheds light on dynamic responses for a number of additional macroeconomic variables. Shocks to consumer sentiments are shown to reduce consumption of both durables and nondurables and increase private saving rates. Moreover, the rise in savings is biased towards safer assets, consistent with a story of precautionary savings. Firms reduce the use of factor inputs, shown by a reduction in capacity utilization and hours worked. Labor market tightness falls both due to a rise in unemployment and a fall in vacancies posted by firms. On the other hand, the negative shock to confidence is non-deflationary and associated with significant increases in asset prices as well. Most importantly,

\textsuperscript{1}The MotherJones database covers August 1982 to June 2017 and we extend this data back to 1960.
a deterioration of consumer sentiments is robustly accompanied by a significant drop in the nominal interest rate. Given the rise in consumer basket and asset prices, monetary policy seems to react directly to the sentiment shock. Indeed, we show that the measures of monetary policy shocks proposed by Romer and Romer (2004) and Gertler and Karadi (2015) react significantly to our identified sentiment shocks.

The identified sentiment shock is distinct from other related shocks in the literature such as “news” and “uncertainty” shocks. If mass shootings carried negative news about future fundamentals of the economy, we would expect them to anticipate a drop in utilization-adjusted total factor productivity (TFP). We see no movement in TFP and are, thus, confident that the confidence shock we identify relates to exogenous “animal spirits” sentiments rather than news inherited in the confidence index. Similarly, our identified shock is not an uncertainty shock since we see no impact effect on measures of uncertainty such as the VIX and Jurado et al. (2015)’s index. By contrast, using Cholesky zero short-run restrictions as an alternative identification strategy to uncover confidence shocks, we observe that utilization-adjusted TFP falls persistently with a lag and uncertainty measures rise on impact, indicating that these identified shocks are confounded with news and uncertainty shocks. Finally, our conclusions on the transmission of sentiment shocks do not hinge on the specific measure of mass shootings used and are robust to various sensitivity analysis.

Economic theory has devoted much attention to the role of sentiments for aggregate fluctuations. Early proponents of the idea that the economy may be susceptible to purely belief-driven fluctuations include Pigou (1926)’s hypothesis of expectations-driven business cycles and Keynes (1936) theory on the importance of “animal spirits” in driving economic behavior. These views are echoed in recent models proposed by Beaudry and Portier (2006), Lorenzoni (2009), Angeletos and La’O (2013) and Blanchard et al. (2013). Similarly, in our theoretical framework we explore the idea of sentiment-driven cycles, looking at a model where temporary but persistent technology shocks determine equilibrium output, but agents receive signals which comprise the true shock and a noise component that we interpret as consumer sentiments. Agents use the Kalman filter to form expectations about the persistent component. Differently from existing studies, we consider a heterogenous agents model with matching frictions in the labor market and nominal rigidities in the goods market.

In this framework, a deterioration in sentiments leads to a temporary fall in output, consumption, and the job finding rate, and a more persistent increase in unemployment coupled
with a temporary increase in inflation. These effects accord well with our empirical findings but contrast most of the predictions of existing models on the effects of noise shocks (see, e.g., Lorenzoni, 2009) that usually characterize sentiment shocks as demand shocks that move output and inflation in the same direction. The mechanism behind these dynamics is based, as in the existing models, on the consumers’ Euler equation. Differently from the existing models, in our heterogenous agents’ model with price rigidities and endogenous unemployment, shocks to sentiments induces a powerful supply-demand feedback mechanism. Countercyclical earnings risk amplifies the negative demand effects of sentiment shocks and monetary policy, instead, moderates them.

In accordance with empirical evidence and as in Ravn and Sterk (2017) a negative technology shock can lead to a persistent fall in output and its components, a persistent rise in unemployment and deflation. Lower productivity sets off lower inflation due to countercyclical earnings risk through a demand channel. The fall in vacancy postings due to lower TFP pushes down job finding rates, increasing agents’ precautionary saving motives. This creates a fall in demand that puts downward pressure on prices offsetting the marginal cost effect of the technology shock that tends to increase prices. On the other hand, a negative sentiment shock temporarily decreases agents’ expectation of future productivity, and induces an expected decline in the job finding rate as the true productivity shock. The expected fall in the job finding rate increases the risk of becoming unemployed and, hence, makes employed households want to save more for precautionary motives and decreases demand, as in the existing literature. From the supply side, lower expected productivity increases real marginal costs for firms, which has a positive impact on inflation. If monetary policy does not react to the sentiment shock and if earnings risk is countercyclical the first effect dominates and inflation falls after a sentiment shock. However, if monetary policy endogenously reacts to the sentiment shock, it reduces the demand channel by decreasing the real rate and the inflation response after a sentiment shock can be non-deflationary, as we observe in the data.

We estimate the deep parameters of the model via indirect inference in order to validate the importance of countercyclical risk and monetary policy in shaping the responses of the macroeconomy after a sentiment shock. In particular we estimate the deep parameters of the model by minimizing the distance between the empirical impulse responses and those generated from simulations of the model. The estimated parameters confirm the importance of countercyclical earnings risk and monetary policy in propagating the macroeconomic effects of sentiments.
Our work is related to recent empirical studies that have tried to identify the macroeconomic effects of sentiment shocks. Mian et al. (2015) use two recent episodes in US history in presidential elections that led to the loss of the incumbent president and identify sentiment shocks as pessimism regarding government policy, resulting when a high share of the county electorate supported the incumbent president and (s)he lost the elections. They conclude that government policy sentiment shocks have limited effects on households’ spending. In a similar vein, Benhabib and Spiegel (2016), using cross-sectional information in state-level data, examine the relationship between state GDP growth and sentiment. Posing that agents in states with a higher share of congressmen from the political party of the sitting president are more optimistic, they show that changes in sentiment are associated with increases in economic activity. Finally, Makridis (2017) contrasts the results of the previous authors and shows that if one accounts for heterogeneity, sentiments about economic activity played an important role in amplifying and propagating the Great Recession. Similar conclusions are also drawn in the work of Lagerborg (2017) that uses school shootings as an instrument to identify sentiment shocks at the local level.

The rest of the empirical literature typically controls for fundamental shocks and treats the residual variation in the measure of confidence as sentiment shocks. Ludvigson (2004) shows that the independent information provided by consumer confidence predicts a small amount of additional variation in future consumer spending. Barsky and Sims (2012) propose that consumer confidence may represent an autonomous change in beliefs that affects economic activity (the “animal spirits” component), or may incorporate information about the future economy (the “news” component) and identify the two components using a VAR framework. They argue that animal spirit shocks unrelated to fundamentals are likely to have an immediate but transitory impact on economic activity and should resemble aggregate demand shocks in the short run. Using this assumption as an identification strategy in their VARs, they find that unexplained innovations in measures of consumer confidence are followed by slowly building and “apparently permanent” changes in the levels of output and consumption. They interpret these results as suggesting that confidence, to a large degree, reflects news about future output and animal spirits have no significant role in inducing cyclical fluctuations. The economic responses to our identified animal spirit shocks do not satisfy the identifying assumptions of Barsky and Sims (2012) and we document that their role in inducing cyclical fluctuations is not negligible.

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. Finally, Section 5 concludes.

\section{Data}

\subsection{Consumer Confidence}

To measure consumer confidence, we use data collected by the University of Michigan in its Survey of Consumer Confidence. This survey has been conducted since the late 1940’s (initially annually, quarterly from 1952 and monthly from 1977) and the extended sample period makes it appealing for time-series analysis. We start our sample in 1960 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 are asked a variety of questions relating to their personal finances and to the aggregate U.S. economy.\footnote{A subset of the respondents are surveyed twice, with a six-month time interval in between, but the majority of subjects are new. Hence, some of the time-variation in the indices is due to rotation of the survey subjects.} Answers are aggregated across respondents and across questions to produce various U.S. consumer confidence indicators. Three broad indices are computed: the Index of Consumer Sentiment (ICS), the Index of Current Economic Conditions (ICC) and the Index of Consumer Expectations (ICE). The first of these is a broad index covering respondents’ views about both current and expected future conditions of their own finances and of the U.S. economy, while the ICS focuses on the current situation and the ICE is based upon the forward-looking questions. We focus on the ICE as the measure of confidence in our analysis because of its forward-looking nature.

The ICE is calculated using responses to three questions: (i) “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?”; (ii) “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?”; and (iii) “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 question, which are commonly referred to as PEXP, BUS12, and BUS5, respectively, the survey subjects are given the choice of a positive, neutral or negative answer. The index is then computed by subtracting the percentage of negative respondents from the percentage of positive respondents.
plus 100, and the scores are normalized relative to the 1966 base period. Figures 1 and 2 plot log ICE alongside log industrial production and the unemployment rate, respectively, where all data are detrended with a fourth order time polynomial. Consumer confidence tends to peak at the late stages of expansionary phases and reach its troughs just prior to economic recoveries. There are exceptions to this, though, including faltering consumer confidence as the U.S. partially recovered from the Great Recession in late 2009 - early 2010. The overall contemporaneous correlation between ICE and detrended industrial production is 32 percent. Unemployment and consumer confidence typically move oppositely but there are, again, exceptions such as the late 1970’s - early 1980’s where the two series appear to commove positively. Nevertheless, there is a somewhat stronger relationship between unemployment and consumer confidence than between consumer confidence and industrial production with a contemporaneous correlation of -47 percent.

2.2 Observables

We use a Proxy VAR identification scheme to estimate the impact of autonomous changes in consumer confidence. We discuss the estimation approach below. The main observables that we focus attention upon are: the civilian unemployment rate, log industrial production, log consumer price index (CPI), and the federal funds rate (FFR). Data is monthly spanning January 1960 to June 2017 and was retrieved from the Federal Reserve Bank of St. Louis (FRED). Data for the unemployment rate and consumer price index for all urban consumers are produced by the Bureau of Labor Statistics. Data for industrial production and the effective federal funds rate are produced by the Board of Governors of the Federal Reserve System.

We also augment the baseline VAR with additional variables. First, we look at the impact on real durable and nondurable goods’ personal consumption expenditures which we obtain from the U.S. Bureau of Economic Analysis. We also study capacity utilization, the percentage of capacity being employed in the manufacturing sector, produced by the Board of Governors of the Federal Reserve System starting in 1967.\(^3\) Finally, we look at the impact on vacancies measured by help-wanted advertising in newspapers (produced by the National Bureau of Economic Research) and

\(^3\)Another measure of utilization is that of the labor input as measured by the average weekly hours per worker. We look at this variable in the on-line appendix. Hours worked are measured as hours for which pay was received of production and nonsupervisory employees in the manufacturing sector, and obtained from the U.S. Bureau of Labor Statistics.
on labor market tightness constructed as the ratio of vacancies to the total number of unemployed (compiled by the U.S. Bureau of Labor Statistics).

In order to further verify our identification of sentiment shocks, we look at the relationship to news and uncertainty shocks. For this purpose we study data on TFP, stock prices, and measures of uncertainty. The S&P common stock price index composite, deflated by CPI, is used to measure real stock prices. Data on quarterly total factor productivity from Fernald (2012), with and without capital utilization adjustments, is interpolated linearly into a monthly frequency. Data proxying for uncertainty that measures market expectation of near-term volatility conveyed by stock index option prices, is taken to be the monthly average of daily values for the VIX starting in 2009, before which it is linked to the VXO starting in 1962. As an alternative, we also look at the proxy for macroeconomic uncertainty proposed by Jurado et al. (2015), focusing on their short-term 1-month index.

All variables except for interest rates are seasonally adjusted. All data except for interest rates and other variables defined as ratios (e.g. labor market tightness) are expressed in natural logarithms.

2.3 Mass Shootings

The instrument we propose for identifying autonomous changes in consumer sentiments is fatalities in U.S. mass shootings. Our primary source for mass shootings in the U.S. is a database constructed by MotherJones (2017) which covers the period August 1982 to June 2017. We extend these data backwards to 1960 using information on mass shootings collected from Wikipedia (2017). The MotherJones (2017) data refers to public mass shootings in which the motive appeared to be indiscriminate killing, satisfying the following criteria: (i) minimum four fatalities (the perpetrator excluded), (ii) the killings were carried out by a lone shooter, and (iii) the shootings occurred in a public place. Also included are a handful of 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. The MotherJones sample contains 90 separate events to which we add 8 events when extending it backwards in time.

There is, however, some disagreement about the measurement of mass shootings. Duwe (2007) argues that the MotherJones data suffer from under-reporting. Duwe defines mass shootings as “incidents that occur in the absence of other criminal activity (e.g., robberies, drug deals, gang
‘turf wars’, etc.) in which a gun was used to kill four or more victims at a public location within a 24-hour period.” This definition appears very similar to the one used by Mother Jones, yet still it contains 40 percent more incidents than Mother Jones’ dataset for the sample in which the two series are comparable. Thus, to ensure robustness we verify our results using the Duwe (2007) data updated by the author to cover the 1960-2016 sample and extended by ourselves with data for the first six months of 2017.

The two sources of data on mass shootings agree on the most serious incidents, listed in Table 1 for the 15 incidents that resulted in 10 or more fatalities. The single worst mass shooting is the 2016 Orlando nightclub massacre in which 49 people lost their lives and 53 were seriously injured. Other very serious incidents include the 1984 San Ysidro massacre at McDonald’s (22 fatalities), Luby’s massacre in Killeen (Texas) in October 1991 where 24 people lost their lives, the Virginia Tech massacre in Blacksburgh (Virginia) in April 2007 (32 fatalities), and the Newtown (Connecticut) school shooting in December 2012 (28 fatalities). On average, there were 7.6 fatalities per shooting in the dataset based upon Mother Jones (754 fatalities deriving from 98 shootings) and 6.85 fatalities per incident according to the updated Duwe (2007) data (1,083 fatalities deriving from 158 incidences).

The upper panel of Figure 3 illustrates the timelines of mass shootings for the extended Mother Jones (2017) data (left) and the updated Duwe (2007) data (right). The Mother Jones data indicate a positive trend in the frequency of mass shootings which increases from approximately one every two years (644 days) on average prior to 1990, to one every five months (158 days) between 1990 and 2000, and further to almost one every two months (76 days) on average in the 2007 - 2017 sample. This marked increase in the incidence of mass shootings is less pronounced, but not entirely absent, in the Duwe data where the frequency rises from one shooting per 219 days prior to 1990 to one shooting per 96 days between 1990 and 2000, and one per 127 days since 2007.

The lower panel of Figure 3 plots mass shooting fatalities for the two samples. Here the trends are more similar, although Duwe’s database contains more fatalities than the Mother Jones-based dataset. Again, there is an increase in the frequency of fatalities which increase from 4.4 (12.6) per year prior to 1990 according to Mother Jones (Duwe), to 15.9 (21.5) per year during 1990-2000, and further to 40.2 (37.5) post 2007. Given this trend in the frequency, we conduct robustness tests with respect to allowing for trends in the fatalities from mass shootings.
2.4 Estimation

We estimate the dynamic causal effects of sentiment shocks by applying the Proxy SVAR estimator introduced by Stock and Watson (2008) and further developed by Stock and Watson (2012) and by Mertens and Ravn (2013). The central idea of the estimator is to use external instruments for the structural shocks of interest in a VAR setting (see Stock and Watson (2018) for a discussion). In our application we use fatalities in mass shootings, discussed above, as a proxy for consumer confidence thereby obtaining an IV estimate of sentiment shocks and their dynamic effects on the vector of observables.

Here we adopt the notation of Stock and Watson (2018). Let $Y_t$ be an $n \times 1$ vector of endogenous observables that are perturbed by an $n \times 1$ vector of structural shocks $e_t$. We assume that $Y_t$ is (second-order) stationary and can be represented as:

$$A(L)Y_t = u_t$$

(1)

where $A(L) = I - A_1L - A_2L^2 - \ldots$, and $L$ is the lag operator, $L^ix_t = x_{t-i}$. The innovations $u_t$ are linear combinations of the structural shocks:

$$u_t = \Theta_0 e_t$$

(2)

where $\Theta_0$ is invertible. Under the stationarity assumption, this implies that:

$$Y_t = \Gamma(L)\Theta_0 e_t$$

(3)

where $\Gamma(L)$ is square summable. The identification problem amounts to identifying $\Theta_0$. In our application we are interested in identifying only a single shock, say $e_1t$, and therefore wish to identify only one column of $\Theta_0$. Let consumer confidence be the first element of the vector of observables, $Y_t$. Identification requires that fatalities in mass shootings, $s_t$, satisfy the following assumptions:

$$E(s_t e_{1t}) = \phi \neq 0 \quad \text{(relevance)}$$

$$E(s_t e_{it}) = 0, \quad i > 1 \quad \text{(exogeneity)}$$

(4)

The relevance condition in (4) says that the proxy is correlated with the structural shock of interest while the exogeneity condition requires the proxy to be orthogonal to other structural
shocks. Imposing the identifying assumptions implies that:

$$\mathbb{E}(s_t u_{1,t}) = \begin{pmatrix} \phi \Theta_{0,11} \\ \phi \Theta_{0,i1} \end{pmatrix}, \ i > 1$$

Subject to these identifying assumptions, the dynamic causal effects of consumer sentiment shocks are identified up to a scale factor. We scale the structural 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 other structural coefficients of interest can then be obtained as:

$$\frac{\mathbb{E}(s_t u_{1,t})}{\mathbb{E}(s_t u_{1,t})} = \Theta_{0,i1}$$

With strong instruments, these coefficients can be estimated by IV regressions of the innovations $u_t$, $\hat{u}_t$, on $\hat{u}_{1,t}$ using $s_t$ as the instrument. The impulse responses then follow from (3) using the sample estimate of the structural sentiment shock, $e_{1,t} = \varphi' u_t$.

3 Empirical Results

We study monthly data for a sample period that spans January 1960 to June 2017. Our benchmark specification is based on a five-variable VAR, $Y_t = [\text{ice}_t, \text{ur}_t, \text{ip}_t, \text{cpi}_t, \text{rnom}_t]$ where $\text{ice}_t$ is the log of ICE, $\text{ur}_t$ is the civilian unemployment rate, $\text{ip}_t$ is the log industrial production, $\text{cpi}_t$ is the log consumer price index, and $\text{rnom}_t$ is the federal funds rate. We also report results for a number of other variables, obtained by adding each of them into the VAR one at a time. We detrend all macroeconomic variables apart from the federal funds rate by a fourth-order polynomial trend. The VAR includes a constant term and 18 lags of the observables.

3.1 Mass Shooting Fatalities as an Instrument

As discussed above, the identification relies on a correlation between fatalities in mass shootings and consumer sentiment, and on the exogeneity assumption.

An existing literature argues that terrorist attacks have an impact on psychological well-being, including confidence. A field experiment of Lerner et al. (2003), in the aftermath of the 9/11 attacks on the Twin towers, suggests that individuals react to such events with very pessimistic
views about their own – and the average American’s – exposure to risk which would indicate some decline in confidence measures. Moreover, policy institutions such as the OECD have highlighted consumer confidence as a key the transmission channels 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. However, while terrorist attacks may satisfy the relevance assumption, 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. Mass shootings, on the other hand, tend not to be connected to a group nor general cause and, as a result, cannot be interpreted as an act of terrorism. Indeed, while Baker et al. (2016a) find that terrorist attacks such as 9/11 prompt spikes in uncertainty, when we use mass fatalities to instrument measures of uncertainty such as the VIX, the F-statistic is close to zero (0.02). Thus, we argue that mass shootings are an appropriate instrument to identify surprise changes in confidence that are orthogonal to second-order moment (uncertainty) shocks.

Impacts on psychological well-being have also been documented for mass shootings. Hughes et al. (2011) evaluate the impact of the Virginia Tech shooting in 2007 on PTSD (post-traumatic stress disorder) symptoms amongst Virginia Tech students in the months after the tragic event. They find that PTSD symptoms were elevated for an extended period even amongst students who were not under direct threat during 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 aftermaths of the 2012 Sandy Hook School shooting and of the 2013 Boston Marathon Bombing. Moreover, according to Fox and DeLateur (2013), although mass shootings take the fewest lives of any other type of homicide, these events induce the most fear in people due to the seemingly random nature of the events and inability to predict and prevent incidents.

An important transmission mechanism through which information about such events are transmitted to a large proportion of the U.S. population is the news coverage of these tragic events. For example, according to Lexis Nexis, a provider of electronic access to legal and journalistic documents, 182 articles have been written 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 (which incurred in 28 fatalities) covering the shootings in main national
news sources in the US. Lankford (2018) studies news coverage of the perpetrators of seven mass killings in the 2013-17 period (including the Orlando nightclub shooter and the perpetrator of the San Bernadino mass shooting) and finds that mass killers received considerable news attention, in many cases more than celebrities such as sports stars. Towers et al. (2015) find that mass killings are contagious in the US through media coverage. Along the same lines, Pappa et al. (2018) show that mass shootings predict future school shootings, consistent with the existence of contagion effects.

We first check the relevance assumption. Figure 4 illustrates the impact of fatalities in mass shootings on ICE estimated from the benchmark VAR which includes 18 lags. We find that mass shootings set off a persistent decline in consumer confidence that is significant for the first 15 months after the incident at the 95 percent level and for 25 months at the 68 percent level. Table 2 reports the F-statistics for the hypothesis that fatalities in mass shootings do not have predictive power for (the innovation to) various measures of consumer confidence. The F-test statistic for instrument exclusion is 11.16 when confidence is measured as ICE, indicating that the instrument appears to be strong (Stock and Yogo, 2005).

Interestingly, the strength of mass shootings as an instrument appears to be higher for the ICE than for the ICS. The weak instrument tests therefore indicate that mass shootings have more significant impact on consumer expectations about the future path on the economy than on the views about the current economic climate (as measured by the ICS). Furthermore, when inspecting the components of ICE, we find that mass shootings has higher predictive power for the index than for its components but also that amongst these, it is more closely related to BUS12 and BUS5 than to PEXP. This shows that the drop in confidence is more closely associated with negative perceptions about the economy (as indicated by BUS5 and BUS12) than to personal economic circumstances, which is useful for our purposes given our focus on the aggregate consequences of autonomous changes in consumer confidence.

Mass shootings are largely unpredictable events and therefore likely to satisfy the exogeneity assumption. First, there is essentially no correlation with the aggregate U.S. unemployment rate (correlation coefficient -0.0003). Moreover, we estimate Poisson regressions for the number

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4These 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).

5In earlier work, Pappa et al. (2018) we show that this is also true for school shootings.
of mass shooting events and mass shooting fatalities and Probit regressions for a mass shooting dummy (equal to one if at least one mass shooting occurred) to check whether the events can be predicted. All of these specifications indicate that the unemployment rate is insignificant (see Table 3). Therefore, no compelling evidence suggests these events are triggered by prevailing conditions in the economy. In line with this, more than 60% of perpetrators have been diagnosed with signs of severe mental illness even prior to committing the mass shootings according to MotherJones (2017), suggesting that the mass shootings are carried out by deeply disturbed individuals with long-term issues.\textsuperscript{6} Moreover, mass shootings occur with a sufficiently 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.

### 3.2 Impulse Responses

We now discuss the dynamic causal effects of autonomous changes in consumer confidence estimated with the Proxy VAR. We evaluate these on the basis of impulse response functions for forecast horizons going up to 60 months. Along with the point estimates, we illustrate the 68 percent and 95 percent confidence intervals.

**Benchmark Results**

Figure 4 shows the identified impulse responses of the benchmark VAR to the identified consumer sentiment shock. The central empirical result is that an autonomous decline in consumer sentiments sets off a persistent deterioration in the economy. Industrial production is roughly unaffected on impact but then starts decreasing persistently reaching its largest decline around a year after the deterioration in consumer sentiments. Thereafter, industrial production starts recovering, but very gradually. At the 95 percent level, the drop in output is significant for 16 months (from 4 to 20 months after the shock). The U-shaped pattern of the response of industrial production\textsuperscript{7} together with the impact of the sentiment shock on confidence itself appears to indicate that there are important economic mechanisms which propagate the worsening consumer sentiments over time.

\textsuperscript{6}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 therefore, we should be cautious with the interpretation of the results". Even if such a link exists, effects on mental health were found primarily for women, while the vast majority of mass shooting perpetrators are men.

\textsuperscript{7}This U-shape is not dissimilar to estimates of the response of output to other structural shocks such as monetary policy shocks.
We also find a significant impact of consumer sentiments on the unemployment rate. Following the decline in consumer confidence, unemployment rises on impact and keeps rising for several months, reaching a maximum increase 18 months after the decline in sentiments, slightly later than the peak decline in output. Thereafter, unemployment starts to recover but at a slow rate, such that unemployment is still significantly above zero for a further 10 months (at the 95 percent level).

On the monetary side, we find that the negative consumer sentiment shock leads to a very persistent rise in prices which is significant at the 68 percent confidence level. 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. At the same time, the short-term nominal interest rate declines on impact and remains below its initial level for more than 2 years. Given the increase in prices and the slow rise in unemployment, the interest rate response appears to indicate that the monetary authority directly responds to consumer sentiment shocks, rather than simply responding indirectly due to the impact of sentiments on the economy. To investigate this in more detail, Figure 5 illustrates the impulse response of the cumulated series of monetary policy shocks identified by Gertler and Karadi (2015) estimated using local projection methods. We find that a deterioration in consumer sentiments induces a persistent decline in the monetary policy shock, with a shape that is quite similar to the impact of the consumer sentiment shock on the federal funds rate itself. Finally, we also regress the Romer and Romer (2004) shock series on our identified sentiment shock. We find that they exhibit significant correlation (with coefficient estimate 0.03 and p-value 0.02).

In order to gauge the results in more detail, we look at the impact on a number of additional variables that we rotate into the VAR one at a time. Figure 6 illustrates the impact on consumption decomposed into non-durables and durables. We find that consumer spending on both non-durables and durables declines significantly upon impact and remains significantly below trend for an extended period after the negative consumer sentiment shock. The peak decline in spending on durables is around three times larger than the corresponding number for spending on non-durables and spending on durables also remains negative for a longer period. Thus, the negative effect on output, as measured by industrial production, is mirrored by consumer spending.

Figure 7 illustrates the dynamic responses of variables relating to the input side of the economy. Hours worked and capacity utilization both decrease following the worsening of consumer
sentiments. Their responses are very similar, both decline upon impact and continue to do so for the first 12 months following the consumer sentiment shock, after which they recover. These responses are significant at the 95 percent level for around a 12-month period. Figure 8 shows the impact on vacancy postings and the equilibrium effect on labor market tightness. Tightness (the ratio of vacancies to unemployment) shows a decline over the first 12 months followed by a slow recovery, similar to the other macroeconomic variables we have discussed above. The deterioration in labor market tightness derives both from the increase in unemployment, as discussed above, and from vacancy postings falling significantly, thus indicating quite severe labor market ramifications of consumer sentiments.

In the Online Appendix we also illustrate how the identified shock affects consumers’ saving behavior and variables such as long-term interest rates, asset prices, and bond yields. Sentiments are shown to significantly increase private saving rates and increase asset prices such as real gold and stock prices. Higher savings appetite also increases the demand for treasuries, consistent with the drop in interest rates observed for the 1-year and 10-year constant maturity Treasury bills. Yields on riskier bonds rise relative to safer bonds to compensate investors for higher risk, as demand rises relatively more for safer assets. The spread of AAA corporate bonds over 10-year treasury bonds is shown to rise whereas the spread between safer AAA bonds and riskier BAA ones falls. All in all, these results support the hypothesis that negative confidence shocks induce a rush to safe assets, emblematic of a “precautionary” savings motive.

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,\textsuperscript{8} that the responses are consistent with consumer confidence innovations mainly reflecting news about future TFP. To check the relationship of the identified sentiment from the Proxy VAR shock with TFP, we augment the vector of observables with the utilization-adjusted TFP series estimated by Fernald and Wang (2016).\textsuperscript{9} We find that TFP is unresponsive to the identified consumer sentiment shock at all forecast horizons at both the 68 percent and the 95 percent level, confirming that our identified sentiment shock is not a news shock about TFP fundamentals. In contrast, estimating a VAR for the same vector of

\textsuperscript{8}These authors do not include TFP in their empirical VAR.

\textsuperscript{9}Updated data on the TFP process can be found on the Federal Fund of San Francisco Webpage: https://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/
observables and imposing a triangular structure on the covariance matrix as in Barsky and Sims (2012) implies that TFP declines significantly at the 68 percent level after about 2 years (see Figure 14), suggesting that the identified innovations to confidence confounds sentiments with fundamental shocks.

Along similar lines, we also analyze the impact of our sentiment shock on measures of “uncertainty.” As previously mentioned, mass shootings are highly insignificant as an instrument for uncertainty, yielding an exclusion F-test statistic that is close to zero. Nonetheless, we augment our benchmark VAR with two commonly-used measures of uncertainty: the VIX and Jurado et al. (2015)’s short-term (1-month) uncertainty index. Figure 13 shows that uncertainty is unresponsive to the identified consumer sentiment shock on impact, and only significantly rises at the 68 percent confidence level for a few months and with a delayed response.10

Finally, one could claim that the identified shocks could be related to future fundamentals (and thereby are not purely animal spirits shocks) since they could signal periods of disputes between democrats and republicans and economic policy uncertainty or could anticipate increases in future taxation due to an increase in spending in policing and security. In the Online Appendix we 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. (2016b)11, consistent with the possibility that news coverage on mass shootings rises and thereby decreases the number of articles on other topics e.g. policy uncertainty. Moreover, we show that our identified shock does not Granger cause the exogenous tax changes series of Romer and Romer (2010) and vice versa. Finally, we instrument autonomous shocks to consumer sentiments with fatalities of young famous celebrities12, whose deaths are clearly unrelated to fundamentals and cannot definitely be thought of as news about future economic conditions. Our results on the effect of sentiment shocks identified using as a proxy young celebrities deaths are very similar to the results we obtain when we identify sentiments shocks using mass fatalities as an instrument, but have much less predictive power for consumer confidence.

To sum up, in this empirical exercise we have demonstrated that fatalities resulting from

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10 This again contrasts the significant rise in uncertainty measures in response to drops in consumer confidence identified using a Cholesky decomposition, which therefore appears to confound sentiments also with uncertainty shocks.

11 Data on EPU are readily available at http://www.policyuncertainty.com/us_monthly.html

12 To weight those deaths we used the number of google hits when we typed the celebrity’s name in brackets in google search. We present the timeline of those deaths as well as their weighting in the Online appendix
mass shootings in the US are a strong instrument for consumer sentiments and, in turn, find that a deterioration in sentiments is recessionary, inflationary, and persistent. We also show a deterioration in consumer sentiments is accompanied by a monetary expansion stemming from a direct reaction of monetary policy to sentiments.

Robustness

As discussed earlier, there is some uncertainty as to the appropriate measure of mass shootings and the frequency of mass shootings appear to have increased over the sample period. Thus, to ensure that our results are not driven by these factors, we perform various sensitivity tests. We present results in the Online Appendix to economize on space.

We show that results are insensitive to using the measure of mass shooting fatalities derived from the Duwe (2007) dataset rather than the MotherJones (2017) data (see Online Appendix Figure 8).

One could argue that not all mass shootings affect confidence in the same way at the national level. Actually, according to Lexis Nexis, it is the mass shootings with more than 10 fatalities that enjoy a widespread coverage in the national press. We therefore present impulse responses when we instrument confidence with the shootings that had a minimum death toll of 10 persons. Results do not differ significantly from our baseline VAR, apart from the responses of industrial production and unemployment exhibiting a somewhat higher persistence (see Online Appendix Figure 9). Results are also robust to weighing the mass shootings by their media coverage in main national and regional news, as reported by Lexis Nexis (see Online Appendix Figure 10).

As noted in Section 2, the frequency – and severity – of mass shootings has changed over the sample period. Results are robust when detrending fatalities in mass shootings with a fourth order polynomial trend (see Online Appendix Figure 11). Results are also insensitive to considering the number of mass shooting events instead of the fatalities resulting from the shootings as an instrument (see Online Appendix Figure 12).

Given that some of these events were unusually large, we have also investigated the sensitivity of our results to excluding one-by-one the 15 mass shootings with a very high number of victims.

13The decline in consumer confidence is slightly more persistent when using the Duwe (2007) dataset and the decrease in industrial production is slightly larger but none of these differences are statistically significant at conventional confidence levels. Moreover, as we report in Table 2, the measure of fatalities in mass shootings derived from Duwe (2007) does not pass the weak instrument test for any of the different confidence indices and, as a result, we prefer not to put too much weight on the reported impulse responses.
(at least 10 fatalities). Online Appendix Figure 13 shows that our results are insensitive to the specific shootings in the sample.

Finally, results are also found to be robust to the lag length in the VAR (Online Appendix Figure 14 plots responses considering 12 lags) and are robust when we first-difference the data instead of using a forth order polynomial trend (see Online Appendix Figure 15). As an additional exercise, we run a placebo test in which we randomly reshuffle the mass shooting fatalities indicator used as the proxy variable and, as expected, find the proxy to be a poor instrument for confidence and an insignificant impact on the other observables in the VAR (see Online Appendix Figure 16).

4 Theory

4.1 The Model

In this section, we relate our empirical results to a theoretical model. We consider a heterogeneous agents model with matching frictions in the labor market and nominal rigidities in the goods market. The economy is subject to fundamental shocks such as productivity shocks and monetary policy shocks. Such shocks trigger fluctuations in the economy over time. However, the economy is also subject to purely informational shocks which, due to imperfect information, have real effects on the economy. Following Lorenzoni (2009), there are two components of productivity, purely transient shocks and persistent changes in productivity. Agents do not observe the two components separately and use a Kalman filter to form expectations about the persistent component. The expectational shocks impact on a signal that agents receive about the persistent component. In this economy, expectational shocks are confused with changes in the persistent component of technology, and therefore induce real effects whose size and persistence depend on a number of wedges in the economy.

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 and face

\[14\] The ordering is drawn from a uniform distribution averaged across 10,000 replications.
uninsurable unemployment risk. Preferences are given as:

\[ U_{i,t} = \hat{E}_t \sum_{s=t}^{\infty} \beta^{s-t} \left( \frac{c_{1-s}^{1-\mu} - 1}{1 - \mu} - \zeta n_{i,s} \right) \]  

(5)

where \( \hat{E}_t x_s = E(x_s|I_t) \) and \( I_t \) denotes the information set at date \( s \). \( 0 < \beta < 1 \) is the subjective discount factor, \( \mu > 0 \) is the degree of relative risk aversion and \( \zeta > 0 \) is a constant parameter. \( c \) denotes a basket of goods defined as:

\[ c_{i,s} = \left( \int_j (c_{i,s}^j)^{1-1/\gamma} dj \right)^{1/(1-1/\gamma)} \]  

(6)

where \( c_{i,s}^j \) is household \( i \)'s consumption of goods variety \( j \) at date \( s \) and \( \gamma > 1 \) denotes the elasticity of substitution between goods. \( n_{i,s} \) denotes the household’s employment status:

\[ n_{i,s} = \begin{cases} 
0 & \text{if unemployed} \\
1 & \text{if employed} 
\end{cases} \]  

(7)

Employed agents earn a real wage \( w_s \) while unemployed agents receive an endowment \( \xi > 0 \).\textsuperscript{15}

**Technology:** Output of variety \( j \) is produced using constant returns technologies:

\[ y_{j,s} = \exp(A_s) \left( z_{j,s} k_{j,s} \right)^\tau n_{j,s}^{1-\tau} \]  

(8)

where \( y_{j,s} \) is firm \( j \)'s output, \( A_s \) is an aggregate productivity shock, \( k_{j,s} \) is the input of capital, \( n_{j,s} \) denotes employment in firm \( j \), \( z_{j,s} \) is the capacity utilization rate, and \( \tau \in [0, 1) \) is the elasticity of output to the input of effective capital.

Firms hire workers in a matching market. We assume that a fixed fraction of existing matches, \( \omega \in (0, 1) \), are terminated every period. New hires are made by posting vacancies, \( v_{j,s} \), at the cost \( \kappa > 0 \) per vacancy. Each vacancy is filled with the probability \( q_s \) which firms take as given. The law of motion of employment is given as:

\[ n_{j,s} = (1 - \omega) n_{j,s-1} + q_s v_{j,s} \]  

(9)

\textsuperscript{15}The fact that all employed workers earn the same real wage anticipates an assumption about wage determination that we make below.
Firms own the capital stock and the law of motion of the capital stock is:

\[ k_{j,s+1} = (1 - \delta(z_{j,s})) k_{j,s} + i_{j,s} \left( 1 - S \left( \frac{i_{j,s}}{i_{j,s-1}} \right) \right) \]  \hspace{1cm} (10)

where \( i_{j,s} \) denotes investment in capital by firm \( j \), \( \delta(z_{j,s}) \) is the capital depreciation rate, and \( S \left( \frac{i_{j,s}}{i_{j,s-1}} \right) \) captures investment adjustment costs. We assume that \( \delta'(z_{j,s}) \), \( \delta''(z_{j,s}) \geq 0 \) so that higher capital utilization rates come at the cost of higher depreciation. The investment adjustment cost function is assumed to be such that \( S(1) = S'(1) = 0 \) and \( S''(1) > 0 \).

Each period, existing matches are dissolved at the end of the period; vacancies are posted at the beginning of the next period; thereafter new matches are formed, and finally production and consumption take place. The measure of new matches between firms looking to hire and unemployed workers are determined by a Cobb-Douglas matching function:

\[ m_s = m^\alpha u_s v_s^{1-\alpha} \]  \hspace{1cm} (11)

where \( m_s \) denotes the measure of new matches, \( m > 0 \) is a constant, \( u_s \) is the measure of unemployed workers, \( v_s = \int_j v_{j,s} dj \) is the measure of aggregate vacancies, and \( \alpha \in (0,1) \) is the elasticity of matches to unemployment. From the matching function, the vacancy filling rate and the job finding rate, \( q_s \) and \( \eta_s \), respectively, are functions of the labor market tightness, \( \theta_s = v_s/u_s \):

\[ q_s = \frac{m \theta_s^{-\alpha}}{m \theta_s^{1-\alpha}} \]  \hspace{1cm} (12)

\[ \eta_s = \frac{m \theta_s^{1-\alpha}}{m \theta_s^{-\alpha}} \]  \hspace{1cm} (13)

from which it also follows that \( q_s = m^{1/(1-\alpha)} \eta_s^{\alpha/(1-\alpha)} \) is a decreasing function of the job finding rate.

**Prices and Wages:** Firms are monopolistically competitive and set the nominal prices of their products, \( P_{j,s} \). They face quadratic price adjustment costs and maximize the objective function:

\[ \Phi_{j,t} = \hat{E}_t \sum_{s=t}^{\infty} \Lambda_{j,t,s} \left[ \frac{P_{j,s}}{P_s} y_{j,s} - w_s n_{j,s} - i_t - \kappa v_{j,s} - \frac{\phi}{2} \left( \frac{P_{j,s}}{P_{j,s-1}} - 1 \right)^2 y_s \right] \]  \hspace{1cm} (14)

where \( \Lambda_{j,t,s} \) denotes the stochastic discount factor of the (owners of the) firms, \( P_s \) is the aggregate
price level, $\phi \geq 0$ denotes the extent of price adjustment costs, and $y_s = \int_j y_{j,s} dj$ is aggregate output. Firms set prices subject to (8)-(9) and subject to the demand functions for their goods:

$$y_{j,s} = \left( \frac{P_{j,s}}{P_t} \right)^{-\gamma} y_t$$

(15)

Given the matching frictions in the labor market, new and existing employment relationships produce a match surplus. It is common to assume that this surplus is divided between workers and firms in a bargaining game. An alternative is to assume that wages are constant or vary systematically with labor market conditions as long as they are consistent with a non-negative match surplus. This latter modeling is convenient in an incomplete markets set-up because it circumvents the issue that wages may be wealth-dependent. For that reason, we assume that the real wage is given as:

$$w_s = \bar{w} \left( \frac{\eta_s}{\bar{\eta}} \right)^\chi$$

(16)

where $\chi \geq 0$ and $\bar{w}, \bar{\eta}$ are constants. (16) accordingly assumes that real wages rise when workers are harder to hire (since $q_s$ is decreasing in $\eta_s$).

**Asset and Budget Constraints:** There are two financial assets, nominal bonds and firm equity, in the economy. As Ravn and Sterk (2017), we adopt a limited participation set-up assuming that only a small share of the agents, denoted by $\Upsilon$, face positive returns from investing in equity.

The flow budget constraint for the agents that can participate in the stock market is:

$$c_{i,s} + b_{i,s} + x_{i,s} \leq w_s n_{i,s} + \xi (1 - n_{i,s}) + \frac{R_{s-1}}{\Pi_s} b_{i,s-1} + \frac{R_{x,s}}{\Pi_s} x_{i,s-1}$$

(17)

while that of those who do not face positive returns from equity investments is:

$$c_{i,s} + b_{i,s} \leq w_s n_{i,s} + \xi (1 - n_{i,s}) + \frac{R_{s-1}}{\Pi_s} b_{i,s-1}$$

(18)

where $b_{i,s}$ denotes purchases of bonds at date $t$, $x_{i,s}$ are equity purchases at date $t$, $R_{s-1}$ is the nominal interest rate, $R_{x,s}$ is the return on equity, and $\Pi_s = P_s / P_{s-1}$ is the gross inflation rate between periods $s - 1$ and $s$. 
Households face the following borrowing constraints:

\[ b_{i,s} \geq -\kappa w_{i,s} \tag{19} \]
\[ x_{i,s} \geq 0 \tag{20} \]

where \( \kappa \geq 0 \) indicates the extent to which debt can exceed flow labor market income. Households are not allowed to go short on equity.

**Monetary Policy:** The nominal interest rate is set by a central bank according to an interest rate rule given as:

\[ R_s = R_{s-1}^{\delta_R} \left( \bar{R} \left( \frac{\Pi_s}{\bar{\Pi}} \right)^{\delta_{\Pi}} \right)^{1-\delta_R} \exp(e_s) \tag{21} \]

where \( \bar{R} \geq 1 \) is a constant, \( \bar{\Pi} \) is an inflation target, and \( e_s \) is an innovation to the interest rate. \( \delta_R \in [0, 1) \) determines the amount of interest rate smoothing while \( \delta_{\Pi} \) determines the response of the central bank to deviations of inflation from its target.

**Information Structure and Stochastic Shocks:** The stochastic process for productivity is given as:

\[ A_s = A_p + \varepsilon^T_s \tag{22} \]
\[ A_p = \rho_A A_{s-1}^p + \varepsilon^P_s \tag{23} \]

where \( A^p \) denotes a persistent component of productivity with persistence parameter \( \rho_A \in (-1, 1) \), \( \varepsilon^P_s \) is the shock to the persistent component of productivity, while \( \varepsilon^T_s \) is a transitory productivity shock. We assume that these shocks mutually orthogonal and normally distributed with means 0 and variances \( \sigma^2_T \) and \( \sigma^2_P \), respectively.

Agents observe \( A_s \) at the beginning of the period but not the transitory and persistent components separately. They do, however, receive a signal about the persistent component:

\[ \Psi^A_s = A_p + \varepsilon^S_s \tag{24} \]

where \( \varepsilon^S_s \) is assumed to be normally distributed with mean 0 and variance \( \sigma^2_S \).
The innovation to monetary policy is given as:

\[ e_s = \varphi e_s^S + \varepsilon_s^R \]  

(25)

where \( \varepsilon_s^R \) is n.i.d. with mean 0 and variance \( \sigma_R^2 \) and is assumed to be orthogonal to \( \varepsilon_s^T, \varepsilon_s^P \) and \( e_s^S \). Agents observe \( e_s \) but not \( \varepsilon_s^R \). When \( \varphi = 0 \), innovations to nominal interest rates reflect only the monetary policy shock \( \varepsilon_s^R \) while \( \varphi \neq 0 \) implies that innovations to interest rates in general will be a mix of sentiments and pure monetary disturbances.

Given this information structure, agents use a Kalman filter to form expectations about \( A_{p_s} \).

Denote the date \( s \) expectation of \( A_{p_s} \) as \( A_{p_{s,s}} \). The solution to the Kalman filter can be then be expressed as:

\[ A_{p_{s,s}} = G A_{p_{s-1,s-1}} + K x_o^s \]  

(26)

\[ x_o^s = (A_s, \Psi_A, e_s)' \]

is the vector of signals with the law of motion:

\[ x_o^s = CA_{p_s} + D \xi_s \]  

(27)

where

\[ C = \begin{pmatrix} 1 & 1 \\ 1 & 1 \\ 0 & \varphi \end{pmatrix}, \quad D = \begin{pmatrix} 1, 0, 0 \\ 1, 1, 0 \\ 0, \varphi, 1 \end{pmatrix}, \quad \xi_s = \begin{pmatrix} \varepsilon_s^T \\ \varepsilon_s^S \\ \varepsilon_s^R \end{pmatrix} \]

\[ G = \rho_A - KC \]

\[ K = \rho_A \Sigma_{\infty} C' (CH_{\infty}C' + V_{\xi})^{-1} \]

\[ V_{\xi} = D'E(\xi'\xi)D \]

and \( H_{\infty} \) is the solution of the Ricatti equation:

\[ H_{r+1} = \rho_A^2 H_r + \sigma_T^2 - \rho_A^2 H_r C' (CH_rC' + V_{\xi})^{-1} CH_r' \]

which can be solved by iteration starting from an initial positive semi-definite guess for \( H_0 \).

**Equilibrium:** Given our assumptions on the asset market structure, in the steady-state with no aggregate shocks agents split into three groups. The first group will be asset-rich households
who have access to the equity market. We assume that there are sufficiently few of these agents that they become so rich that they drop out of the labor market (due to the fixed participation cost $\zeta$). The second group are unemployed asset-poor workers. These agents expect income to increase when they find a job and therefore would like to issue debt but are prevented from doing so by the borrowing constraint (19). The third group will be the employed asset-poor households. These agents perceive the risk of job loss, have an incentive to save in the steady-state, and therefore the steady-state real interest rate has to satisfy their Euler equation. Since these agents face idiosyncratic risk, the steady-state real interest rate will be lower than $1/\beta$.

This latter implication means that asset rich households drop out of the bond market because they face no idiosyncratic risk and therefore purchase equity only (with a steady-state expected return on $1/\beta$).

We focus on the equilibrium properties of the model in the vicinity of the steady-state where inflation is on target. Furthermore, we assume that $\bar{\pi} = 1$ so that the central bank targets price stability. Shocks are assumed sufficiently small that employed agents have an incentive to save (so that the real interest rate satisfies their Euler equation) and that the asset rich households do not wish to participate in the labor market.

In equilibrium, firms therefore firms set the same prices and make the same investment, capacity utilization and employment decisions. The equilibrium conditions can then be summarized by:

\[
(c^e_s)^{-\mu} = \hat{E}_s \beta \frac{R_s}{\Pi_{s+1}} \left( (1 - \omega) (1 - \eta_{s+1}) \right) \left( c^e_{s+1} \right)^{-\mu} + \omega (1 - \eta_{s+1}) \left( c^m_{s+1} \right)^{-\mu} \tag{28}
\]

\[
\gamma mc_s = \phi (\Pi_s - 1) \Pi_t - \hat{E}_s \beta \left( \frac{c^r_{s+1}}{c^e_s} \right)^{-\mu - \mu} y_{s+1}^s \phi (\Pi_{s+1} - 1) \Pi_{s+1} + \gamma - 1 \tag{29}
\]

\[
mc_s = \frac{1}{\exp(A_s)} \left( \frac{w_s}{(1 - \tau) (z_s k_s / n_s)} \right)^\tau + \frac{\kappa}{q_s} - \hat{E}_s \beta \left( \frac{c^r_{s+1}}{c^e_s} \right)^{-\mu} \left( 1 - \omega \right) \frac{c^r_{s+1}}{q_{s+1}} \tag{30}
\]

\[
1 = \beta \hat{E}_t^{-\mu} \left( \frac{c^r_{s+1}}{c^e_s} \right)^{-\mu} \left[ \lambda_{s+1} (1 - \delta (z_s)) + \tau \exp(A_{s+1}) z_{s+1} (z_{s+1} k_{s+1})^{\tau - 1} n_{s+1}^{1 - \tau} \right] \tag{31}
\]

\[
1 = \lambda_s \left( 1 - S \left( \frac{i_s}{i_{s-1}} \right) - S' \left( \frac{i_s}{i_{s-1}} \right) \frac{i_s}{i_{s-1}} \right) + \beta \hat{E}_s \left( \frac{c^r_{s+1}}{c^e_s} \right)^{-\mu} \lambda'_{s+1} S' \left( \frac{i_{s+1}}{i_s} \right) \left( \frac{i_{s+1}}{i_s} \right)^2 \tag{32}
\]

\[
\delta' (z_s) \lambda_s = \exp(A_s) (z_s k_s)^{\tau - 1} n_s^{1 - \tau} \tag{33}
\]
in addition to (21), the laws of motion of the shocks, and the solution to the Kalman filtering problem discussed above. \( c^e_s, c^u_s, \) and \( c^r_s \) denote equilibrium consumption levels of asset poor employed agents, asset poor unemployed agents, and entrepreneurs which are given as:

\[
\begin{align*}
  c^e_s &= \bar{w}\left(\frac{\eta_s}{\bar{\eta}}\right)^\chi \\
  c^u_s &= \xi \\
  c^r_s &= \frac{1}{\Upsilon}(\exp(A_s)(z_sk_s)^\tau n_s^{1-\tau} - \kappa v_s - w_s n_s - i_s) + \xi
\end{align*}
\]

\( n_s = \frac{1}{1-\Upsilon} \left( \int n_{j,s}dj \right) \) denotes aggregate employment while \( \lambda \) is the multiplier on the capital accumulation equation normalized by entrepreneurs’ marginal utility of consumption. Equation (28) is the Euler equation for asset poor employed workers which, on top of the standard intertemporal savings motive, adds a precautionary motive due to idiosyncratic unemployment risk. Equation (29) is the optimal price setting condition for the firms where \( mct \) denotes marginal costs defined in equation (30). Equation (31) is the condition for optimal capital accumulation, (32) is the condition for investment, and (33) is the first-order condition for optimal capacity utilization.

In addition, the matching function implies that:

\[
q_s v_s = \eta_s \left( 1 - n_{s-1} + (1 - \omega) n_{s-1} \right)
\]

and the law of motion of employment is given as:

\[
n_s = (1 - \omega) n_{s-1} + \eta_s (1 - n_{s-1} + \omega n_{s-1})
\]

We solve the model by a log-linearization and using a method of undetermined coefficients.

**Sentimental Business Cycles:** We now investigate the extent to which the model can account for key features of the data. The central difference between the model presented here and the models analyzed by Lorenzoni (2009) and Barsky and Sims (2012) is the presence of incomplete markets.\(^{16}\) In addition, we also allow consumer sentiments, the noise shock, to directly impact on monetary policy, and we have introduced matching frictions in the labor market.

\(^{16}\)Moreover, these authors focus on permanent technology shocks while we allow these to be persistent but transitory.
In the models of Lorenzoni (2009) and Barsky and Sims (2012) inflation and output (and consumption) move together giving the consumer sentiment shock the interpretation of a “demand” shock. In these models, the short run dynamics of consumption is mainly determined by changes in household expectations about longer term productivity. When a negative sentiment shock arrives, expected income drops which drives down consumption. Evidently, this is inconsistent with the empirical results that we have discussed earlier because these indicate a negative correlation between consumption and inflation conditional upon a decline in consumer sentiments. Perhaps even more importantly, Barsky and Sims (2012) show that sentiment shocks essentially have no discernible impact on output in the standard NK model.

The incomplete markets model, however, can address this issue. Consider a log-linearization of the employed workers’ Euler equation (and let \( \bar{x} \) denote the steady-state value of \( x \)):

\[
-\mu \hat{c}_t = \bar{E}_t \left( \hat{R}_t - \hat{\Pi}_{t+1} \right) - \mu \beta \bar{R} \hat{E}_t \hat{c}_t - \beta \bar{R} \Psi \hat{E}_t \eta_{t+1}
\]

where \( \Psi = \omega \eta \left( (\xi/\bar{w})^{-\mu} - 1 \right) - \chi \omega \mu (1 - \bar{\eta}) \) is an incomplete markets endogenous earnings risk wedge that arises due to a precautionary savings motive.

This Euler equation differs from the complete markets version because of: (i) discounting - the fact that future consumption enters with the coefficient \( \mu \beta \bar{R} < \mu \) rather than \( \mu \); and (ii) the last term on the right hand side which relates to the precautionary savings wedge. This wedge represents the endogenous earnings risk that is driven by two forces: First, the job finding rate changes over time. A drop in the job finding rate increases the risk that a currently employed worker is unemployed next period (because finding a new job is harder in case the current match is dissolved) which induces a precautionary savings motive. Through this channel, precautionary savings stimulates demand in booms and reduces demand in recessions. On the other hand, a higher job finding rate increases the real wage which implies that employed workers face a larger income loss should they lose their job. This channel, thus, stabilizes demand as the economy fluctuates between good and bad times. As discussed by Ravn and Sterk (2018), precautionary savings provides amplification when \( \Psi > 0 \) (countercyclical risk) and stabilization when \( \Psi < 0 \) (procyclical risk). Which of these channels dominates depends primarily on the drop in income upon job loss, \( \xi/\bar{w} \), and the degree of real wage cyclicality, \( \chi \). Larger income losses upon unemployment, or lower real wage elasticity make it more likely that \( \Psi > 0 \) and vice versa. Finally, notice that when \( \Psi = 0 \) there is no endogenous risk feedback.
Estimation: In order to understand what drives the empirical impulse responses through the lens of our model, we estimate key structural parameters. We adopt a simulation estimator. Initially, we split the vector of structural parameters into $\Theta_1$ and $\Theta_2$. $\Theta_1$ contains structural parameters that we calibrate rather than formally estimate and we discuss these below. $\Theta_2$ is the vector of parameters that we estimate. The key idea behind the estimator is to find combination of parameters in $\Theta_2$ that, given $\Theta_1$, implies the closest fit to the moments in the data that we estimated in Section 3.

Formally, $\Theta_2$ is found by solving a quadratic minimization problem:

$$
\hat{\Theta}_2 = \arg \min_{\Theta_2} \left[ \left( \hat{\Lambda}^d_T - \Lambda^m_T (\Theta_2|\Theta_1) \right)' \Sigma_d^{-1} \left( \hat{\Lambda}^d_T - \Lambda^m_T (\Theta_2|\Theta_1) \right) \right]
$$

where $\hat{\Lambda}^d_T$ denotes the vectorized empirical responses, $\Lambda^m_T (\Theta_2|\Theta_1)$ are the equivalent estimates from the theoretical model and $\Sigma_d^{-1}$ is a weighting matrix. $\hat{\Lambda}^d_T$ contains the impulse responses of the benchmark VAR for a forecast horizon of 36 months in addition to the $F$–statistic for the first-stage regression. We add this last moment because it helps identifying the measurement error that we discuss below.

We find $\Lambda^m_T (\Theta_2|\Theta_1)$ by estimating Proxy SVARs on artificial data generated by the model. Recall that the benchmark empirical VAR contains 5 observables, consumer confidence, industrial output, unemployment, CPI prices and the nominal interest rate. The latter four of these have natural counterparts in the model. As far as consumer confidence is concerned, the mapping between the data and theory is less clear. Here we choose to measure consumer confidence by $A^p_{s,s}$, i.e. by the agents perception of the level of persistent technology. This measure of confidence is affected both by fundamental shocks and by the sentiment shocks and is important indicator of the agents’ expectations about the future path of the economy. We then use a noisy measure of the sentiment shocks as the instrument for $A^p_{s,s}$ and derive the estimates of the relevant moments.

The model equivalents of the empirical impulse responses are generated as follows:

1. Given $\Theta_1$ and $\Theta_2$, generate 100 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 $\hat{\Lambda}^d_T$). Eliminate the first $R$ observations. Denote this $T \times 5$ vector of the model-based observables for the $j$’th artificial sample by $\tilde{X}_j (\Theta_2|\Theta_1)$. For each sample, let $\tilde{\varepsilon}_j^S (\Theta_2|\Theta_1)$ denote the $T \times 1$ vector of sentiment shocks.
2. Add a small amount of measurement error to $\tilde{X}_j(\Theta_2|\Theta_1)$. Let $\tilde{X}_j^j(\Theta_2|\Theta_1)$ denote the resulting artificial samples of $X$. Detrend the artificial data with a fourth order time polynomial as in the data.

3. Add measurement to $\tilde{\varepsilon}_j^S(\Theta_2|\Theta_1)$ to obtain $\tilde{\varepsilon}_j^S(\Theta_2|\Theta_1) = \tilde{\varepsilon}_j^S(\Theta_2|\Theta_1) + m_j$ where $m_j$ is assumed to be normally distributed with mean zero and variance $\sigma_{m}^2$.

4. For each artificial dataset, estimate the model equivalents of the empirical Proxy SVAR moments using $\tilde{\varepsilon}_j^S(\Theta_2|\Theta_1)$ as an instrument for $A_{s,s,j}^p(\Theta_2|\Theta_1)$. Let $\Lambda_{T}^{m}(\Theta_2|\Theta_1)^j$ denote the simulated equivalents of the vector of empirical moments for the $j$’th artificial sample.

5. Average the moments over the 100 replications, yielding $\Lambda_{T}^{m}(\Theta_2|\Theta_1)$.

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. Following Hall et al. (2012), we compute the standard errors of the vector $\Theta_2$ from an estimate of its asymptotic covariance matrix as

$$
\Sigma_{\Theta_2} = \Lambda_{\Theta_2} \frac{\partial \Lambda_{T}^{m}(\Theta_2|\Theta_1)^{'}}{\partial \Theta_2} \Sigma_{d}^{-1} \Sigma_{s} \Sigma_{d}^{-1} \frac{\partial \Lambda_{T}^{m}(\Theta_2|\Theta_1)}{\partial \Theta_2} \Lambda_{\Theta_2}
$$

where

$$
\Lambda_{\Theta_2} = \left[ \frac{\partial \Lambda_{T}^{m}(\Theta_2|\Theta_1)^{'}}{\partial \Theta_2} \Sigma_{d}^{-1} \frac{\partial \Lambda_{T}^{m}(\Theta_2|\Theta_1)}{\partial \Theta_2} \right]^{-1}, \quad \Sigma_{s} = \Sigma + \frac{1}{100^2} \sum_{j=1}^{100} \Sigma_{j}
$$

$\Sigma$ denotes the full covariance matrix of the impulse responses estimated in Section 3 ($\Sigma_{d}$ contains the diagonal elements of $\Sigma$), and $\Sigma_{j}$ is the covariance matrix of the $j$’th replication of the model based impulse responses.

**Calibration and Estimation Results:** We calibrate parameters that either are hard to estimate or which we believe there are good grounds for calibrating rather than estimating. The vector of parameters that we calibrate is $\Theta_1 = (\overline{R}, \xi, \mu, \overline{u}, \eta, \kappa, \tau, \delta (1), \gamma, \sigma_{p}^2)$. The parameters are calibrated to a monthly frequency and are summarized in Table 4.

We set steady-state gross inflation equal to one. $\overline{R}$ therefore determines the steady-state (gross) real interest rate. We calibrate this parameter to correspond to a 4 percent annual net
real interest rate, $\bar{R} = 1.04^{1/12}$. Next, we calibrate the degree of risk aversion to $\mu = 1$, a standard value in the literature. We calibrate $\xi$ so that it equals 85 percent of the steady-state real wage implying that consumption (and income) falls by 15 percent upon job loss. This value is a compromise between the estimates of Hurd and Susann (2011) and Chodorow-Reich and Karabarbounis (2016) who estimate that consumption drops by 12 percent and 20 percent, respectively, upon job loss.

We set the steady-state unemployment rate equal to 6 percent and the monthly job finding rate $\eta$, equal to 34 percent. The unemployment rate is close to the average rate observed in the U.S. in the post WWII sample while the job finding rate implies an average 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, $\omega$, is 3.3 percent. Next, we assume that the vacancy cost parameter, $\kappa$, is consistent with an average hiring cost of 4.5 percent of the quarterly wage.

On the technology side, we set the labor income share equal to 63 percent, a value close to what has been observed in the U.S. over the last 30 years. $\delta(1)$ is calibrated to match a capital-output ratio of 28 at the monthly frequency, which implies that $\delta(1) = 0.0061$. $\delta'(1)$ is instead normalized so that steady-state capacity utilization equals 1. We set the elasticity of substitution between intermediate goods equal to 6 which implies a 15 percent mark-up in the steady-state. We normalize the variance of persistent technology shocks to $\sigma_p^2 = 0.001^2$. Given that our estimation targets the impulse responses, we can identify only the relative variances of the shocks. Hence, the calibration of $\sigma_p^2$ simply serves as an anchor.

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

\[
\beta = \frac{1}{\bar{R} \left( 1 + \omega (1 - \eta) \left( (\frac{\xi}{\mu})^{-\mu} - 1 \right) \right)}
\]

which gives us a value of $\beta = 0.993$.

The vector of parameters that we estimate is $\Theta_2 = (\alpha, \phi, \chi, \delta''(1), S''(1), \delta_\pi, \delta_R, \rho_A, \sigma_T, \sigma_S, \sigma_R, \psi)$. Figure 18 illustrates the simulated impulse response functions of the model together with their empirical counterpart. Apart from the impact response of unemployment, which is smaller than in the data, we find that the model reproduces very well the shape and sizes of the Proxy SVAR estimates of the impact of sentiment shocks.
Table 5 contains the point estimates of $\Theta_1$ and also the implied endogenous earnings risk wedge $\Psi$. We find an elasticity of the matching function with respect to unemployment, $\alpha$, of 63.4 percent which is close to standard values in the macro labor literature. This value of $\phi$ which determines the degree of nominal rigidities is estimated to 158.4. 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 $\gamma/\phi$ while the corresponding value in the Calvo model is $(1 - \varpi)(1 - \varpi\beta)/\varpi$ where $1/(1 - \varpi)$ is the average contract length. Our estimates imply an average contract length of 5.7 months which is in the lower range of values typically assumed in the NK literature but consistent with empirical estimates of the degree of price stickiness.

A key parameter is $\chi$ which determines the elasticity of the real wage to the job finding rate. High values of this parameter will tend to imply that the endogenous earning risk wedge is procyclical which induces stabilization while low values of the parameter more likely imply a countercyclical risk wedge which leads to amplification. We find that $\chi = 0.0221$. Together with the other parameters, this implies that $\Psi = 0.0015$ so that the endogenous earnings risk is countercyclical. Next, we find very mild capacity utilization costs, $\delta''(1) = 0.18$, while the investment adjustment costs are more substantial at $S''(1) = 166.5$.

The parameter estimates associated with the monetary policy response function imply that $\delta_\pi = 1.021$ and that $\delta_R = 0.489$, so that there is some interest rate smoothing. We also find that $\varphi = 0.034$ which implies that the central bank reacts to noise shocks even in the absence of inflationary pressures.

Finally, we estimate the parameters of the stochastic processes. $\rho_A$ is estimated to be 91 percent at the monthly frequency. This value is rather low relative to standard estimates in the literature (recall that the model is estimated at the monthly frequency). We find a large value of the standard deviation of transitory technology shocks relative to the persistent component, $\sigma_T^2 = 0.0124^2$. The variance of noise shocks and of (pure) monetary policy shocks are instead estimated to be quite low, $\sigma_S^2 = 0.0019^2$ and $\sigma_T^2 = 0.0007^2$. Finally, we find that in order to match the $F$–statistic for the first stage of the Proxy SVAR that we simulate, we need substantial measurement error in the noise shock, $\sigma_m^2 = 0.0113^2$.

**Implications:** We now explore some properties of the estimated model. Figure 19 illustrates the
expectations that agents form about the persistent component of technology conditional on the innovations to the four structural shocks. 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’ expectations perceive a hump-shaped response of $A_{s,s}$ as there initially is some uncertainty about whether the increase in total productivity derives from persistent or temporary shocks. Eventually as the increase in technology persists, after 5-6 months, agents become convinced the observed higher value of $A$ 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.

Figure 20 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 set off by the noise shock induces a long recession in the economy which sees unemployment rising for around half a year before starting to recover but at a very slow rate. Thus, the model introduces a substantial propagation of the noise shocks through both expectations and through behavioral responses. At the same time as unemployment rises, the model implies a decline in output which derives both from falling employment, a decline in capacity utilization and lower investment in real capital. Alongside this decline in activity, the model also implies lower consumption.

Interestingly, in line with the empirical estimates, the model implies that inflation rises while nominal interest rates decline. This may seem puzzling because the negative noise shock sets off a contraction in demand. However, the noise shock is a perceived shock to the supply side in the economy that increases marginal costs and, hence prices. Also, recall that we allow the noise shock to impact directly on monetary policy. In particular, because $\psi > 0$, the central bank cuts the nominal interest rate in response to the decline in consumer sentiments. This cut in nominal interest rates also has inflationary implications which dominate the downward pressure on inflation induced by the demand reduction.

Since we estimate that the endogenous earning risk wedge is positive, the model incorporates an amplification mechanism through precautionary savings. In particular, in response to the
negative noise shock, the job finding rate declines. Employed agents therefore perceive a higher risk that they may not be employed next period (since the chance of finding a new job should they lose their current one declines). In response to this increase in earnings risk, employed households increase their desired savings which puts downward pressure on real interest rates and on real marginal costs. This decline in aggregate demand leads firms to hire less which induces a further decline in the job finding rate.

It is this 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 21 contrasts the response of unemployment in the benchmark model with the response in a version of the model where we increase the real wage elasticity in order to induce a procyclical endogenous earnings risk wedge. When we introduce procyclical endogenous risk, the response of unemployment is extremely mild because the incentive to increase the savings rate for precautionary reasons is neutralized.

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. Moreover, the economic contraction is accompanied by a rise in inflation as well as a monetary expansion, suggesting that monetary authorities react directly to sentiment shocks. In other words, for a given set of fundamentals, a drop in consumer confidence would instigate a drop in interest rates. We then show that these dynamics are consistent with an incomplete markets model with sticky prices, and labor market frictions, where consumer sentiments are modeled as noisy signals about future TFP as in Lorenzoni (2009).

The evidence from our estimated Proxy VAR provides empirical support in favor of a causal effect of confidence shocks, or in other words, the existence of “sentimental” business cycles.
Our results are at odds with Barsky and Sims (2012) and Fève and Guay (2016), which claim that animal spirit shocks can have at most small and temporary effects. The evidence instead sides with Forni et al. (2017), who contest that these shocks can have sizable and long-lasting macroeconomic effects. We are able to show that exogenous confidence shocks, identified using mass shooting fatalities as an instrument, induce significant fluctuations in economic activity and trace out the dynamic responses for a wide set of macroeconomic variables.

Finally, we have proposed an heterogeneous agent new Keynesian model with search and matching frictions and imperfect information to account for our empirical findings. The model suggests the countercyclical risk wedge and the reaction of monetary policy to sentiments to be important determinants for the transmission of sentiment shocks in the economy.
References


6 Appendix

6.1 Data

Table 1: Mass Shootings With 10 or More Fatalities

<table>
<thead>
<tr>
<th>Incident</th>
<th>Location</th>
<th>Date</th>
<th>Fatalities</th>
<th>Injuries</th>
</tr>
</thead>
<tbody>
<tr>
<td>University of Texas Tower shooting</td>
<td>Austin, Texas</td>
<td>August 1966</td>
<td>18</td>
<td>31</td>
</tr>
<tr>
<td>San Ysidro’s McDonalds massacre</td>
<td>San Ysidro, California</td>
<td>July 1984</td>
<td>22</td>
<td>19</td>
</tr>
<tr>
<td>U.S. Postal Service shooting</td>
<td>Edmond, Oklahoma</td>
<td>August 1986</td>
<td>15</td>
<td>6</td>
</tr>
<tr>
<td>GMAC massacre</td>
<td>Jacksonville, Florida</td>
<td>June 1990</td>
<td>10</td>
<td>4</td>
</tr>
<tr>
<td>Luby’s massacre</td>
<td>Killeen, Texas</td>
<td>October 1991</td>
<td>24</td>
<td>20</td>
</tr>
<tr>
<td>Columbine High School massacre</td>
<td>Littleton, Colorado</td>
<td>April 1999</td>
<td>13</td>
<td>24</td>
</tr>
<tr>
<td>Red Lake massacre</td>
<td>Red Lake, Minnesota</td>
<td>March 2005</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>Virginia Tech massacre</td>
<td>Blacksburg, Virginia</td>
<td>April 2007</td>
<td>32</td>
<td>23</td>
</tr>
<tr>
<td>Binghampton shootings</td>
<td>Binghampton, New York</td>
<td>April 2009</td>
<td>14</td>
<td>4</td>
</tr>
<tr>
<td>Fort Hood massacre</td>
<td>Fort Hood, Texas</td>
<td>November 2009</td>
<td>13</td>
<td>30</td>
</tr>
<tr>
<td>Aurora Theatre shooting</td>
<td>Aurora, Colorado</td>
<td>July 2012</td>
<td>12</td>
<td>70</td>
</tr>
<tr>
<td>Newtown School shooting</td>
<td>Newtown, Connecticut</td>
<td>December 2012</td>
<td>28</td>
<td>2</td>
</tr>
<tr>
<td>Washington Navy Yard shooting</td>
<td>Washington, D.C.</td>
<td>September 2013</td>
<td>12</td>
<td>8</td>
</tr>
<tr>
<td>San Bernadino mass shooting</td>
<td>San Bernadino, California</td>
<td>December 2015</td>
<td>14</td>
<td>21</td>
</tr>
<tr>
<td>Orland Nighclub massacre</td>
<td>Orlando, Florida</td>
<td>June 2016</td>
<td>49</td>
<td>53</td>
</tr>
</tbody>
</table>

Table 2: F tests for Alternative Confidence Indices

<table>
<thead>
<tr>
<th>Instrument</th>
<th>Mass Fatalities Coefficient</th>
<th>IV exclusion F- statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mother Jones Fatalities</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ICS</td>
<td>-1.12***</td>
<td>8.80</td>
</tr>
<tr>
<td>ICE</td>
<td>-1.66***</td>
<td>11.16</td>
</tr>
<tr>
<td>BUS5</td>
<td>-1.57***</td>
<td>4.55</td>
</tr>
<tr>
<td>BUS12</td>
<td>-0.94**</td>
<td>5.99</td>
</tr>
<tr>
<td>PEXP</td>
<td>-0.24**</td>
<td>3.74</td>
</tr>
<tr>
<td><strong>Duwe Fatalities</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ICS</td>
<td>-0.74**</td>
<td>5.41</td>
</tr>
<tr>
<td>ICE</td>
<td>-1.02**</td>
<td>5.87</td>
</tr>
<tr>
<td>BUS5</td>
<td>-0.84</td>
<td>1.90</td>
</tr>
<tr>
<td>BUS12</td>
<td>-0.46</td>
<td>2.00</td>
</tr>
<tr>
<td>PEXP</td>
<td>-0.10</td>
<td>0.89</td>
</tr>
</tbody>
</table>
Figure 1: Consumer Confidence vs. Industrial Production

Note: Both variables are detrended using a 4th order polynomial trend.

Figure 2: Consumer Confidence vs. Unemployment

Note: Both variables are detrended using a 4th order polynomial trend.
Figure 3: Timeline of Mass Shootings and Fatalities

Table 3: Exogeneity of Mass Shootings

<table>
<thead>
<tr>
<th>Model</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Probit</td>
<td>Poisson</td>
<td>Poisson</td>
</tr>
<tr>
<td>Mass Shooting Dummy</td>
<td>0.003</td>
<td>-5.6e4</td>
<td>0.031</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.064)</td>
<td>(0.717)</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.948</td>
<td>-7.005</td>
<td>(4.546)</td>
</tr>
<tr>
<td></td>
<td>(0.400)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>690</td>
<td>690</td>
<td>690</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.0003</td>
<td>0.0005</td>
<td>0.0002</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
6.2 VAR Impulse Responses

Figure 4: Consumer Sentiment Shock IRF - Benchmark

Figure 5: Consumer Sentiment Shock IRF - Gertler-Karadi Cumulative Monetary Policy Shock
Figure 6: Consumer Sentiment Shock IRF - Consumption

Figure 7: Consumer Sentiment Shock IRF - Input Variables

Figure 8: Consumer Sentiment Shock IRF - Labor Market Tightness
Figure 9: Consumer Sentiment Shock IRF - Long-Term Interest Rates

Figure 10: Consumer Sentiment Shock IRF - Corporate Bond Spreads

Figure 11: Consumer Sentiment Shock IRF - Asset Prices
Figure 12: Consumer Sentiment Shock IRF - Total Factor Productivity

Figure 13: Consumer Sentiment Shock IRF - Uncertainty

Figure 14: Cholesky SVAR Augmented with Adjusted TFP
Figure 15: Cholesky SVAR Augmented with Jurado’s Uncertainty Index

Figure 16: Cholesky SVAR Augmented with Real Stock Prices
6.3 Model Impulse Responses

Table 4: Calibrated Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R/\Pi$</td>
<td>real interest rate</td>
<td>$1.04^{-(1/12)}$</td>
</tr>
<tr>
<td>$\Pi$</td>
<td>steady state gross infl. rate</td>
<td>1</td>
</tr>
<tr>
<td>$\mu$</td>
<td>relative risk aversion</td>
<td>1</td>
</tr>
<tr>
<td>$1 - \frac{c_u}{c_e}$</td>
<td>income loss upon unemployment</td>
<td>0.15</td>
</tr>
<tr>
<td>$\bar{u}$</td>
<td>steady state unemployment rate</td>
<td>0.06</td>
</tr>
<tr>
<td>$\bar{\eta}$</td>
<td>steady state job finding rate</td>
<td>0.34</td>
</tr>
<tr>
<td>$\omega$</td>
<td>exogenous job turnover rate</td>
<td>0.033</td>
</tr>
<tr>
<td>$(\kappa/\bar{q})/(3\bar{w})$</td>
<td>hiring cost as a fraction of quarterly wage</td>
<td>0.045</td>
</tr>
<tr>
<td>$1-\tau$</td>
<td>labor share</td>
<td>0.63</td>
</tr>
<tr>
<td>$k/y$</td>
<td>capital-output ratio</td>
<td>28</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>elasticity of substitution differentiated goods</td>
<td>6</td>
</tr>
<tr>
<td>$\sigma_P$</td>
<td>std. dev. of persistent technology shock</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Table 5: Parameter Estimates (std errors to come)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta''(1)$</td>
<td>elasticity of depreciation rate to capacity utilization</td>
<td>0.18</td>
</tr>
<tr>
<td>$S''(1)$</td>
<td>elasticity of adjustment costs</td>
<td>166.5</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>matching function elasticity</td>
<td>0.634</td>
</tr>
<tr>
<td>$\phi$</td>
<td>price adjustment costs</td>
<td>158.4</td>
</tr>
<tr>
<td>$\chi$</td>
<td>elasticity of real wage to job finding rate</td>
<td>0.0221</td>
</tr>
<tr>
<td>$\delta_{\Pi}$</td>
<td>inflation coefficient on Taylor rule</td>
<td>1.021</td>
</tr>
<tr>
<td>$\delta_R$</td>
<td>inertia in Taylor rule</td>
<td>0.489</td>
</tr>
<tr>
<td>$\varphi$</td>
<td>reaction of monetary policy to noise</td>
<td>0.034</td>
</tr>
<tr>
<td>$\Phi$</td>
<td>Implied risk wedge</td>
<td>0.0015</td>
</tr>
<tr>
<td>$\rho_A$</td>
<td>persistence of technology shock</td>
<td>0.910</td>
</tr>
<tr>
<td>$\sigma_T$</td>
<td>std. dev. of transitory shock</td>
<td>0.0124</td>
</tr>
<tr>
<td>$\sigma_S$</td>
<td>std. dev. of noise shock</td>
<td>0.0019</td>
</tr>
<tr>
<td>$\sigma_R$</td>
<td>std. dev. of monetary shock</td>
<td>0.0007</td>
</tr>
<tr>
<td>$\sigma_m$</td>
<td>std. dev. of measurement error for noise</td>
<td>0.0113</td>
</tr>
</tbody>
</table>
Figure 17: Model Impulse Response Bands to True TFP Shock
Figure 18: Simulated Responses to Sentiment Shock From Estimated Model

Figure 19: Theoretical Impulse Responses to Sentiment Shock
Figure 20: Theoretical Impulse Responses to True TFP Shock

Figure 21: Theoretical Impulse Responses of Unemployment to True TFP Shock