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Abstract

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Sentimental Business Cycles*

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July 7, 2020

Abstract

We use fatalities in mass shootings in the U.S. as an instrument for autonomous declines in consumer confidence to estimate the dynamic causal effects of sentiment shocks. Declining confidence is recessionary and sets off a severe contraction in the labor market, while having less evident nominal effects. Sentiment shocks explain a non-negligible part of cyclical fluctuations. We demonstrate that in a model with heterogeneous agents, nominal rigidities and search-and-matching frictions, a wave of pessimism can take the economy from a normal state on a path towards a high-unemployment sunspot limit, inducing dynamics that resemble the empirical patterns.

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1 Introduction

An extensive empirical literature in macroeconomics has investigated the sources of impulses to the business cycle. The large majority of papers on this topic has provided causal evidence on the impact of shocks related to economic fundamentals such as monetary and fiscal policy shocks, technology and investment-specific shocks, oil price shocks, etc. (see the recent comprehensive survey of Ramey, 2016). However, under a variety of conditions, the economy may also be affected by shocks unrelated to economic fundamentals, such as expectational errors or 'animal spirits' but there is very little – if any – *direct* evidence on the impact of such shocks and their propagation. This paper provides empirical estimates of the causal effects of unexpected changes in consumer sentiments and offers a theoretical underpinning of these results. We find that deteriorating consumer sentiments are recessionary especially in terms of their impact on the labor market. Sentiment shocks explain a non-negligible part of cyclical fluctuations. In a model with heterogeneous agents, nominal rigidities and search-and-matching frictions, countercyclical income risk gives rise to multiple long-run equilibria including both high and low unemployment steady-states. We demonstrate that stochastic sunspot equilibria generate similar dynamics to those in the data when a wave of pessimism takes the economy from a 'normal' state on a path towards a high-unemployment sunspot limit.

The central challenge to estimating shocks unrelated to economic fundamentals is the translation of this concept into functions of observables. We address this issue by, first, focusing upon autonomous changes in consumer sentiments measured on the basis of variations in survey evidence on consumer expectations. Secondly, we assume that news about events unrelated to economic fundamentals can be used for extracting autonomous movements in consumer expectations. Operationally, we follow an extensive literature that has focused on the Index of Consumer Expectations (ICE) produced by the University of Michigan in its Survey of Consumer Confidence. The ICE contains views of survey respondents regarding the future outlook for their own and the U.S. economy's conditions. These views reflect information about (current and future) fundamentals but may also contain an autonomous component, consumer sentiments, the component we aim to identify.

We implement the Mertens and Ravn (2013) proxy SVAR estimator and propose to use fatalities in mass shootings in the U.S. as an instrument for consumer sentiment shocks. The key idea is that such tragic events - while unrelated to economic fundamentals - may trigger a wave of pessimistic consumer sentiments which can impact on the economy. We focus on mass shootings with seven or more fatalities which occurred in a public space and were unrelated to gang crime and to personal disputes. From 1965 to November 2018, there were no less than 618 fatalities in such shootings stemming from 47 separate events, with the most lethal one being the 2017 Las Vegas Strip massacre (58 fatalities) and other notorious ones including the Columbine High School massacre in April 1999 and the Virginia Tech massacre in April 2007. Notably the frequency and severity in terms of victims has increased over time; almost 20 percent of the total mass shootings (8 shootings) that resulted in over 30 percent of total fatalities (197 fatalities) occurred in the last three years of the sample.

We study monthly data and focus on the sample period spanning 1965:1 to 2007:8—which excludes the period when shootings become very frequent as well as the Great Recession. Our benchmark VAR consists of the ICE, industrial production, the unemployment rate, the consumer price level, the short-term nominal interest rate, a measure of macroeconomic uncertainty and real stock market prices. Fatalities in mass shootings are used as a proxy for autonomous changes in the ICE, which we refer to as consumer "sentiment shocks", and we show that the proxy passes weak instrument tests. After a negative sentiment shock, consumer confidence declines persistently and significantly so for around 12-15 months.

Deteriorations in consumer confidence triggered by a sentiment shock induce a rise in the civilian unemployment rate which remains significantly elevated for more than a year. The worsening labor market conditions are also reflected in reductions of labor market tightness and vacancy postings. Parallel to the worsening labor market conditions, lower consumer confidence triggers a contraction in industrial production and in consumption of both non-durable and durable goods. The impact of the sentiment shock is less evident on financial market indicators where we find a decline in short term nominal interest rates after a negative sentiment shock and a small and short-lived effect on the consumer price index (CPI). Furthermore, macroeconomic uncertainty and stock prices, as well as utilization-adjusted total factor productivity (TFP) do not react significantly to the shock in sentiments at any time horizon.

We demonstrate robustness of our results by deriving dynamic causal effects on the basis of a local projection instrumental variable (LP-IV) estimator. Using the forecast variance ratio (FVR) statistic proposed by Plagborg-Moller and Wolf (2019), we show that confidence shocks explain a significant fraction of cyclical fluctuations in consumer expectations, labor market indicators, and industrial production, while they appear less relevant for variations in asset markets and in inflation. In particular, as much as 30 percent of the FVR at the six-month horizon in the ICE stems from sentiment shocks. For industrial production, these shocks explain 20-25 percent of the FVR at horizons between 6 months and one year. As regards unemployment, vacancies and labor market tightness, sentiment shocks explain around 20 percent of their FVRs for forecast horizons from 3 to 16 months.

We then ask whether such sentiment-driven cycles can be accounted for by theory. We examine an incomplete markets model with nominal rigidities and labor market matching in which endogenous countercyclicality of income risk and prices rigidities can pave the way for multiple long-run equilibria. The risk channel impacts on precautionary savings and, when risk is countercyclical, amplifies the impact of shocks to the economy. When risk is sufficiently countercyclical, there may be stochastic sunspot equilibria including self-fulfilling paths towards a pessimistic sunspot limit that displays high unemployment and low output. We interpret sentiment shocks as a wave of pessimism that takes the economy on such a path and sentimental business cycles as reflecting such temporary episodes of low activity cum high unemployment. The average path of the economy after agents turn pessimistic shares many characteristics with our empirical estimates of the causal effects of consumer sentiment shocks including the predominant impact on the labor market.

Our work adds to a long line of studies on the role of expectations and sentiment shocks for aggregate fluctuations which has recently received a considerable amount of interest. One line of work has focused on the impact of "news" shocks, see Beaudry and Portier (2014) for an extensive survey. Lorenzoni (2009), Blanchard *et al.* (2013), and Faccini and Melosi (2019) build on imperfect information models in which sentiments are modeled as noisy signals about shocks related to economic fundamentals. Angeletos and La'O (2013) and Angeletos *et al.* (2018) examine the impact of higher-order beliefs in settings with heterogeneous priors which can accommodate waves of optimism and pessimism due to frictional coordination. Our focus on stochastic sunspots is more akin to the early literature on cyclical fluctuations resulting from "animal spirits" in models that feature multiple equilibria, such as Diamond (1982), Cass and Shell (1983) and Benhabib and Farmer (1994).

The evidence from our IV estimates provides empirical support in favor of a causal macroeconomic effect of sentiment shocks. Our results are at odds with Barsky and Sims (2012) and Fève and Guay (2019), who find that animal spirit shocks have small and temporary effects on activity. Our findings instead agree with Lorenzoni (2009), Beaudry *et al.* (2011), Forni *et al.* (2017), Levchenko and Pandalai-Nayar (2020), Enders *et al.* (2020) and Chahrour and Jurado (2018) who conclude that these shocks can have sizable and long-lasting macroeconomic effects. Relative to the previous studies, we seek direct evidence on the effects of sentiment shocks. Our work is also related to recent empirical studies that have tried to identify sentiment shocks in cross-sectional studies. Mian *et al.* (2015) highlight that government policy sentiment shocks have limited effects on household spending, while Benhabib and Spiegel (2019) and Makridis (2019) show that sentiments play an important role in propagating cycles in the economy, consistent with our results in the aggregate data.

The remainder of the paper is organized as follows: Section 2 describes the data and the empirical framework. Section 3 presents our empirical results. Section 4 contains the theoretical analysis and Section 5 concludes.

2 Data and Empirical Methodology

This section discusses the data and presents the empirical methodology we apply to derive causal estimates of the impact of sentiment shocks.

2.A Consumer Confidence

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

Each month approximately 500 randomly selected persons are surveyed by phone and asked a variety of questions regarding their own personal finances as well as the economic and financial situation of the U.S. economy.[1] Answers are aggregated across respondents and across questions to produce three broad indices: the Index of Consumer Sentiment (ICS), the Index of Current Economic Conditions (ICC) and the Index of Consumer Expectations (ICE). The ICC focuses on answers to the questions that concern the current state of the respondents own financial situation and of the U.S. economy, the ICE is based upon forward-looking questions, while the ICS is a broad index covering respondents' views about both current and expected future conditions. We focus on the ICE because of its expectational nature.

The ICE summarizes responses to the following three questions:

1. "Now looking ahead–do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?";

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

3. "Looking ahead, which would you say is more likely–that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?"

For each of these three questions, commonly referred to as PEXP, BUS12, and BUS5, respectively, the survey subjects choose between positive, neutral or negative answers. The index is then computed as 100 plus the difference in the percentage of positive and negative respondents and the scores are normalized relative to the 1966 base period.

It is well documented that consumer confidence fluctuates with macroeconomic conditions. Figure 1 shows the time series of detrended ICE alongside industrial production and the unemployment rate. The ICE is correlated with industrial production and unemployment (the correlation coefficients are 0.33 and -0.28, respectively) and tends to peak, but not always, at the late stages of expansionary phases, reaching its trough just prior to economic recoveries. Carroll *et al.* (1994) show that the ICS has predictive power for consumption growth (controlling

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

for income); Matsusaka and Sbordone (1995) report that the ICS Granger causes GDP; and Ludvigson (2004) finds that consumer confidence has predictive power for consumer spending, when controlling for the consumption-wealth ratio. Such evidence, however, does not reveal whether consumer confidence variations derive from shocks of various sorts to the economy which may have predictive power for consumption and other variables, or whether *autonomous* shocks to consumer confidence influence the state of the economy. The instrumental variable (IV) framework proposed below aims at telling these two possibilities apart.

2.B Mass Shootings

We use fatalities in mass shootings as an instrument for consumer sentiments shocks. The idea is that this constitutes a source of bad news which in itself should not derive from economic fundamentals. The primary source of data on mass shootings from 1982 is a database compiled by MotherJones (2020). Data prior to 1982 were obtained from databases collected by Duwe (2007) and by The-Violence-Project (2019). We supplement these with information we obtained from Wikipedia (2020) and cross-check with news and court reports.

The MotherJones (2020) database documents public mass shootings in which the motive appeared to be indiscriminate killing, satisfying the following criteria: (i) minimum three fatalities, (ii) the killings were carried out by a lone shooter, (iii) the shootings occurred in a public place, (iv) perpetrators who died or were wounded during the attack are not considered in the victim counts. The database includes also a handful of cases known as "spree killings" in which the killings occurred in more than one location in a short period of time, otherwise fitting the aforementioned criteria. For consistency we adopt their criteria in our search for additional events in the period prior to 1982.

We focus on larger mass shootings with minimum seven fatalities excluding the perpetrator. From January 1965 to November 2018, there were 47 such events with a total of 618 fatalities implying that these shootings on average resulted in 13 fatalities.[2] Perhaps the two best known events are Columbine High in April 1999 where 12 students and one teacher were murdered and the Virginia Tech Massacre in 2007 when an undergraduate student murdered 32 people on campus. The single worst mass shooting is the 2018 Las Vegas Strip Massacre in which 58 people were killed and 546 people were injured, followed by the Orlando Nightclub Massacre in June 2016 when 49 people lost their lives and 53 were seriously injured.

Figure 2 illustrates the timeline of mass shootings fatalities over the whole sample together with NBER recessions (grey bars). The most serious incidents are listed in the Online Appendix. There is no correlation between mass shootings and recessions, as well as no signs of seasonality. The frequency of mass shootings has increased over time from an average of one shooting ap-

[2]The Online Appendix provides a comprehensive review of the mass shootings data including less lethal events with between 3 and 6 victims. We also perform robustness analyses using alternative instruments.

proximately every 1000 days prior to 1990, to one every 521 days between 1990 and 2000, and to one every 260 between 2000 and 2015, escalating to one shooting every 160 days in the last three years of the sample. The number of fatalities in mass shootings per month has also increased. Prior to 2015, each shooting involved on average 11 fatalities, a figure which has increased to 26 per shooting since 2016. Given the increase in the frequency of shootings, we control for a trend in mass shooting fatalities. The Online Appendix shows, however, that the results are robust to leaving out such a trend.

2.C Macroeconomic Aggregates

We study the impact of sentiment shocks on a wide range of macroeconomic aggregates. The key observables that we examine are the civilian unemployment rate, industrial production, the consumer price index, the federal funds rate, the short-term (12-month) uncertainty index of Jurado *et al.* (2015), and real stock prices (the Standard & Poor's 500 index divided by the CPI). We also look at labor market indicators, such as vacancy postings and labor market tightness, as well as at consumption of non-durables and durables. Finally, we look at the impact of the sentiment shock on utilization-adjusted total factor productivity and economic policy uncertainty. The Online Appendix includes precise definitions and sources of all the data.

Our benchmark sample spans January 1965 to August 2007, but we also report results when including post-2007 data. We focus on the shorter sample for two main reasons. First, as highlighted above, the frequency of mass shootings increases significantly towards the end of the sample. As we will discuss later, this has implications for the relevance of the instrument. Second, we leave out the Great Recession and its aftermath because the depth of the downturn and the lower floor on the short term nominal interest rate are likely to have changed the behavior of agents relative to other periods. However, we present further results in the Online Appendix for alternative sample periods and show that our main results are robust to including post-2007 data although, as expected, sampling uncertainty increases.

2.D Methodology

We base our benchmark analysis on identifying autonomous changes in consumer sentiments using the proxy SVAR estimator developed by Stock and Watson (2012) and by Mertens and Ravn (2013). The central idea is to use external instruments for the structural shocks of interest in a VAR setting. We also show robustness of the results to using an alternative local projection IV approach (see, e.g., Ramey and Zubairy (2018), Fieldhouse *et al.* (2018), Stock and Watson (2018)).

Let $\mathbf{Y}_t$ be an $n \times 1$ vector of endogenous observables perturbed by an $n \times 1$ vector of structural shocks, $\mathbf{e}_t$, that are mutually orthogonal. $\mathbf{Y}_t$ is assumed to be second-order stationary and can be represented as:

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

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

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

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

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

where $\Gamma(\mathbf{L}) = \mathbf{A}(\mathbf{L})^{\mathbf{-1}}$ is square summable. We are interested in characterizing the causal impact of a single shock and therefore in obtaining a single column of $\mathbf{\Theta}_0$. Without loss of generality, we order consumer confidence first in the vector of observables. Let $\mathbf{s}_t$ be a proxy for $\mathbf{e}_{1t}$, the structural shock of interest (we use the notation $\mathbf{s}_t$ for $S_t - proj\,(S_t|\mathbf{W}_t)$ where S_t is the proxy, W_t is the history of Y_t, and $proj(x|z)$ denotes the projection of x on z). The proxy SVAR imposes the following identifying assumptions:

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

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

The relevance condition in (4) requires correlation between the proxy and the unobserved structural shock of interest, while (5) imposes orthogonality with other structural shocks. If the identifying assumptions hold, it follows that:

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

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

We scale the impulse responses so that the sentiment shock corresponds to a one percent decline in the consumer confidence index, i.e. $\Theta_{0,11} = 1$. The remaining structural coefficients of interest are then obtained as:

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

We implement the estimator with a 2SLS procedure and estimate the coefficients above by regressing $\widehat{\mathbf{u}}_t$ on $\widehat{\mathbf{u}}_{1t}$ using $\mathbf{s}_t$ as the instrument. With these coefficients at hand, the impulse responses can be computed from equation (3). We compute standard errors guided on the evidence of instrument strength.[3]

[3]With strong instruments, inference can be carried out using a Delta method estimator of the covariance

3 Empirical Results

The benchmark specification of the vector of observables is:

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

where ic_t is the natural logarithm of the ICE, u_t is the civilian unemployment rate, ip_t is the natural logarithm of industrial production, cpi_t is the natural logarithm of the consumer price index, ffr_t is the federal funds rate, unc_t is the natural logarithm of Jurado *et al.* (2015)'s 12-month macroeconomic uncertainty index, and sp_t represents the natural logarithm of real stock prices. The VAR includes a constant and the lag length is set to 18 months.[4] We detrend all variables apart from the federal funds rate with fourth-order time polynomials. We seasonally adjust using the Census Bureau's X13 tool all variables that were not already seasonally adjusted by the data source provider (except for shootings and the federal funds rate). The Online Appendix contains results for alternative measures of confidence, no detrending of the data and controlling for seasonality in shootings.

3.A Mass Shooting Fatalities as an IV

Relevance

The underlying idea of the proxy is that mass shootings, while unrelated to fundamentals, can influence the economy because they may impact on households' views about the future path of the economy, which are reflected in consumer sentiments. This does require, of course, that households are aware of the events. Mass shootings are likely to enter the information set of many households through news and through social interactions and therefore may possibly impact on behavior. Mass shootings receive significant news coverage, reaching a large portion of the U.S. population. For example, according to LexisNexis (2020), a provider of electronic access to legal and journalistic documents, main national news sources in the U.S. printed no less than 182 articles on the Fort Hood Massacre in Texas in 2009 (13 fatalities) and 156 articles on the Newtown school shooting in Connecticut in 2012 (28 fatalities).[5] Lankford (2018) studies news coverage of the perpetrators of seven mass killings in the 2013–17 period and finds that mass

matrix, else other covariance estimators are available, see Mertens and Ravn (2019) for a discussion.

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

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

shooters in many cases received more news attention than even celebrities such as sports stars.[6]

There is also direct evidence that mass shootings impact on psychological well being: Hughes *et al.* (2011) evaluate the impact of the Virginia Tech shooting in 2007 on post-traumatic stress disorder (PTSD) symptoms amongst Virginia Tech students in the months following the tragic event. They find that PTSD symptoms were elevated for an extended period even amongst students who were not under direct threat during the shooting. Clark and Stancanelli (2017) document a decline in subjective well-being across the U.S. in the aftermath of the 2012 Sandy Hook School shooting. Furthermore, Fox and DeLateur (2013) show that, while mass shootings account for the fewest loss of lives compared to any other type of homicide, these events induce the most fear in people due to their seemingly random nature and the inability to predict and prevent incidents. Beyond mass shootings, other acts of violence such as terrorist attacks might also impact on psychological well-being. Abadie and Gardeazabal (2003) document that terrorism induces significant economic costs. However, while terrorist attacks may satisfy the relevance condition, the exclusion restriction is arguably less credible because of their direct economic costs in terms of spending on policing and national security.

Given this evidence, we examine whether the instrument satisfies the relevance condition. Table 1 reports the outcomes of the first-stage F-statistics for the null hypothesis that the instrument has no explanatory power for consumer confidence. We report F-test statistics for a variety of specifications and for the null of standard conditional homoscedasticity (and no serial correlation) as well as the Montiel-Olea and Pflueger (2013) HAR-robust F-statistics.

We first check the outcome of the weak instrument tests for our benchmark 1965:1–2007:8 sample. Next, we include data up to end of 2015 and, finally, we look at the sample ending in November 2018. For the 1965:1–2007:8 benchmark sample the standard F-statistic is equal to 12.0, while it is 17.6 when we correct for heteroscedasticity. Including data up to the end of 2015, the standard F-statistic remains approximately unchanged at 11.2 while the HAR version falls to 5.2 which is, nonetheless, still well above the five percent critical value (3.8). By contrast when the sample is extended up to November 2018, both versions of the F-statistic decline and the HAR-robust F-statistic falls to 2.5. The most likely reason for this is the stark increase in the frequency of mass shootings at the end of the sample, which makes it less reliable as an instrument.

The MotherJones (2020) database also contains information on mass shootings with between three and six fatalities. Making use of this alternative instrument with three or more fatalities, the F-statistics decline but still pass the relevance test. The weaker correlation between this instrument and consumer confidence is likely caused by the less serious incidents attracting less

[6] Given the mechanism we want to highlight, we could use media coverage instead of mass fatalities as the instrument for shootings. We have opted for the former, since this measure is arguably more objective and consistent throughout the sample period. Instead, media coverage data (e.g., LexisNexis (2020) or Vanderbilt (2020) on tv coverage) is very noisy. Notice that when we consider shootings with more than seven fatalities, using media coverage measures and mass fatalities as instruments produces comparable results.

attention. We also report the weak instrument test when replacing the number of fatalities with dummy variables which equal one if a mass shooting with seven or more fatalities occurred and zero otherwise. In this case, the F-statistics are 10.6 and 16.5, respectively, thus, indicating no issues of weak instruments.

The second block of Table 1 examines the relevance of the instrument for alternative measures of consumer confidence. We consider the ICC, ICS, BUS5 and BUS12 indices which were discussed in Section 2 above. We find that fatalities in mass shootings remain useful as an instrument for the ICS, while the instrument loses relevance when considering the ICC, i.e. consumers' perceptions of current circumstances. Focusing on the BUS12 and BUS5 indices, fatalities in mass shootings remain useful as a proxy for BUS12 but less so for BUS5, suggesting that these events appear to affect consumer perceptions of the near rather than the far future. The next rows in Table 1 report F-test values when we consider alternative specifications of the vector of observables, using CPI inflation instead of the CPI level, and when we exclude real stock prices (SP500) or uncertainty (U12) or both from the observables. None of these modifications alter the conclusions about the relevance of the instrument.

Figure 3 displays the point estimate (black line) as well as 68 percent and 90 percent confidence intervals for the ICE response to the identified sentiment shock. Given the weak instrument test outcomes for our baseline specification, we could use the Delta method for computing confidence intervals. We opted to be more conservative and use the procedure suggested by Montiel-Olea *et al.* (2020) for inference. This method is asymptotically valid in the face of weak instruments which is the case in some of the robustness exercises. To further gauge robustness, Figure 3 also shows point estimates (blue lines) of the impulse response function for confidence from specifications in which we exclude one-by-one each of the 24 mass shootings with seven or more fatalities in our sample. This helps understanding whether our results are not driven by particular events.

The point estimate is highly robust and ICE falls persistently after a negative sentiment shock. Eight months after the drop in confidence, only 50 percent of the initial drop has dissipated and it takes around 18 months before the point estimate of the drop in confidence has returned to its initial level. Taking sampling uncertainty into account, the decline in consumer confidence is significant for 13 months at the 90 percent level and for 15 months at the 68 percent level.

Exogeneity

The use of fatalities in mass shootings as an instrument for consumer sentiment shocks rests on the assumption that they can be considered exogenous to other economic factors. Given the random nature of mass shootings, this is a plausible assumption. Pappa *et al.* (2019) show that mass shootings are not predictable by past economic conditions. Our identification strategy requires that they are orthogonal to *current* economic conditions. There is no compelling evidence that these events are triggered by prevailing conditions in the economy. In line with this, more than

60 percent of perpetrators have been diagnosed with signs of severe mental illness even prior to committing the mass shootings according to MotherJones (2020).[7]

One might also consider whether mass shootings could impact on macroeconomic aggregates directly, i.e. through consumer sentiments only. Sadly, despite their tragic nature, mass shootings occur on a regular basis and each shooting is unlikely to trigger direct intervention (such as increased spending on security) which could question the exclusion restrictions we have imposed. Further, supporting our assumption that fatalities in mass shootings impact on the economy through consumer sentiments, we find fatalities to be a weak instrument for uncertainty and for stock prices.

3.B Sentiment shocks

Figure 4 depicts the historical realizations of the identified sentiment shocks together with the NBER recessions. To make the plot easier to digest, we also depict the 5-month centered moving average of the shock series.

The identified shock appears to turn negative prior to or at the very start of NBER recessions. This is particularly apparent for the early 1990s recession where the identified shock turns very negative from the onset of the recession until the late summer of 1990. In line with this, McNees (1992) attributes this recession partially to loss of consumer and business confidence as a result of the 1990 oil price shock. Similar drops in confidence lead the recession in the early 1980s. According to Seymour and Schneider (1987), this period was characterized by a decline in consumers' confidence in institutions. For instance, in mid-summer of 1979 Jimmy Carter called attention when he lectured the nation about the existence of a "crisis of confidence" that "stroke at the very heart and soul and spirit of the national will." We also notice a sustained period of negative confidence shocks in the aftermath of the 9/11 attacks in 2001 and many economists and institutions (e.g. Lenain *et al.* (2002)) attribute an important role to confidence after this episode.

3.C Dynamic Casual Effects

Impulse responses:

Figure 4 plots the impulse responses for the baseline specification. An autonomous decline in consumer sentiments sets off a persistent deterioration in the economy. As discussed above, consumer confidence falls for around 13-18 months. In parallel with this, industrial production declines gradually but persistently with a one-month delay reaching its largest fall around 7

[7]Some studies link economic recessions to mental health problems. An in-depth literature review by Parmar *et al.* (2016) concludes that many studies suffer from of biases and their results should be taken with caution. Yet, even if such a link exists, effects on mental health were found primarily for women, while the vast majority (97.5 percent) of mass shooting perpetrators are men.

months after the consumer sentiment shock[8]. Unemployment also displays a hump-shaped response, reaching its peak 13 to 15 months after the drop in sentiments, whereafter it starts to recover. It is particularly evident that the unemployment dynamics are highly persistent.

On the monetary side, the negative consumer sentiment shock leads to a persistent rise in prices which is significant in the first couple of months but thereafter only at the 68 percent level and only for approximately a year. The short-term nominal interest rate declines with a lag and remains below its initial level for more than two years. Turning to stock market prices, we find that the decline in consumer sentiments gives rise to a persistent drop in equity prices which is, however, statistically insignificant. Likewise, we find little evidence of a significant impact on macroeconomic uncertainty. Macroeconomic uncertainty only rises in the first few months at the 68 percent level.

In order to explore impacts on macroeconomic aggregates in more detail we introduce other variables into the VAR one at a time. Given the significance of the impact on unemployment, we first take a deeper look at other key labor market variables. Of particular interest is the impact on firms' hiring activities and on the overall state of the labor market. Figure 6 shows that labor market tightness, the ratio of vacancy postings to unemployment, falls for a long period and significantly so for around 15 months following the worsening consumer sentiments. Similarly, the number of job vacancies falls significantly for more than a year even at the 90 percent level. In summary, we find severe labor market ramifications of sentiment shocks.

Figure 6 also reports the impact on household real spending on non-durable and durable consumption goods. The decline in aggregate activity produced by deteriorating consumer sentiments is associated with reduced private sector consumption. Non-durables consumption falls on impact and remains depressed for more than a year. The response of durable consumption is more severe yet less persistent.

Other shocks

An important check on our results is the extent to which the identified consumer sentiment shock may be confounded with other shocks. Barsky and Sims (2012) study the impact of innovations to consumer confidence using a Cholesky decomposition of the covariance matrix on quarterly U.S. data and argue, on the basis of a DSGE model, that the responses are consistent with consumer confidence innovations mainly reflecting news about future TFP.

We now augment the vector of observables with the utilization-adjusted TFP series of Fernald and Wang (2016). We find that TFP is unresponsive to the identified consumer sentiment shock (the response is statistically insignificant at all forecast horizons at the 90 percent level, see Figure 6). Hence, the identified sentiment shock is unlikely to be a news shock about TFP.

[8]In results not presented here for the sake of brevity, we find that the impulse response functions of variables relating to the intensive margin of factor input use, such as hours worked per worker and capacity utilization, follow similar paths to the responses of industrial production.

Along the same lines, it is interesting to relate the identified sentiment shock to an economic policy uncertainty shock since one might believe that mass shootings could signal periods of disputes between democrats and republicans. Similarly, mass shootings might be perceived to impact on future taxation due to an increase in spending on policing and security. In Figure 6 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.* (2016). This evidence is consistent with news coverage on mass shootings rising and thereby decreasing the number of articles on other topics including policy uncertainty. Moreover, uncertainty as measured by the VIX index of U.S. stock market options volatility is not significantly impacted. In the Online Appendix we further show that our identified shock does not Granger cause the exogenous tax changes series of Romer and Romer (2010).

Finally, in order to stress the benefits of our identification procedure we present in the Online Appendix the responses to a sentiment shock identified by imposing a triangular structure on the covariance matrix as in Barsky and Sims (2012). The identified shock by means of the Cholesky decomposition induces a significant increase in uncertainty on impact and stock prices fall significantly for 10 months after the shock. Furthermore, when using the Cholesky decomposition, TFP falls while economic policy uncertainty and the VIX rise significantly after a negative sentiment shock. This suggests that the identified innovations to confidence obtained using a Cholesky decomposition confounds sentiments with shocks to economic fundamentals. We also present in the Online Appendix a placebo exercise in which we replace the proxy variable with randomly reshuffled mass shooting fatalities. As expected, this proxy variable is a poor instrument for confidence and the responses of all observables turn out to be insignificant.

3.D Local Projections

A major advantage of the proxy SVAR estimator adopted above is that it provides a parsimonious description of the data where the dynamic causal effects are functions of $\mathbf{A}(\mathbf{L})$ and the identified column of $\mathbf{\Theta}_0$ only. On the other hand, the VAR model does impose linearity and invertibility so that the shocks can be derived as linear functions of the current and past values of the observables. Invertibility may be an issue for our analysis to the extent that consumer confidence reacts to news about future fundamentals. One concern in this respect is that we find hump shaped responses of both industrial production and unemployment to the identified shock.

For robustness analysis we therefore also derive dynamic causal effects on the basis of a local projection estimator, which imposes less restrictive assumptions. In particular, we apply the LP-IV estimator (previously used by Fieldhouse *et al.* (2018), Ramey and Zubairy (2018), Stock and Watson (2018)). Plagborg-Moller and Wolf (2019) show that this estimator can be used can be used to derive forecast error variance decompositions under a recoverability condition which allows the shock of interest to also depend on future values of the observables.

For identification we now add to condition (5):

$$\mathbb{E}\left(\mathbf{s}_t \mathbf{e}_{i\tau}\right) = 0,\ \forall i, \tau \neq 0 \tag{7}$$

which states that the proxy should be orthogonal to leads and lags of the structural shocks.

The impulse response functions for a horizon going up to H periods are derived as the estimates of $(\gamma_h)_{h=0}^{H}$:

$$y_{i,t+h} - y_{i,t-1} = \alpha_h + \gamma_h ic_t + \varphi_h\left(\mathbf{L}\right)\mathbf{Y}_{t-1} + \varepsilon_{i,t+h},\ h = 0, .., H \tag{8}$$

where y_{it} is the i'th variable of $\mathbf{Y}_t$. This relation is estimated using $\mathbf{s}_t$ as an instrument for ic_t using a two-stage least squares procedure. We specify the control variables, $\mathbf{Y}_{t-1}$, exactly as in the proxy SVAR application. Hence, the first stage is identical to above.

Figure 7 illustrates the impulse responses of the observables included in the benchmark VAR, estimated using the LP-IV estimator with 18 lags of the observables as controls as above (with 68 and 90 percent Newey-West confidence bands). We show the impulse responses for up to $H = 24$ months. The results are qualitatively very similar to those in Figure 4 and show that a decline in consumer sentiments induces a contraction in the economy.

Figure 7 shows that in response to a negative sentiment shock, consumer confidence falls for about eight months, and significantly so for the first six months. Thereafter, confidence recovers. In response to this, output falls for around a year and significantly so for the first 8 months. While the impact on aggregate activity is less persistent than the one obtained from the VAR, the peak decline estimated with local projections is actually larger than what we found using the VAR estimator, hence, illustrating the sizeable impact of consumer sentiments on the economy. We also confirm that a negative consumer sentiment shock induces a weakening of the labor market. In particular, the unemployment rate rises significantly for almost a year and we show in the Online Appendix that also vacancies and labor market tightness fall significantly. As for output, the LP-IV responses are larger at peak impact but less persistent than the ones we derived using the proxy SVAR estimator.

Consistent with Figure 4, the LP-IV results indicate a small response of consumer prices to the decline in consumer confidence while the nominal interest rate falls. Stock prices do not respond significantly to the shock, while uncertainty increases with a lag and its response is significant two to five months after the shock. In the Online Appendix we present estimates of impulse responses using the LP-IV methodology for the rest of the variables we present in the SVAR exercise.

3.E Business cycle contributions

We now examine the extent to which sentiment shocks may matter for business cycle variations. Building on the robustness of our results using LP-IV methods, we evaluate the contribution of the shocks by imposing the associated weaker assumption of recoverability, using the forecast variance ratio (FVR) statistic developed by Plagborg-Moller and Wolf (2019):

$$\mathbf{FVR}_{i,h} = 1 - \frac{\mathbf{var}\left(y_{i,t+h} \middle| \left(\mathbf{Y}_{\tau}\right)_{-\infty\leq\tau\leq t}, \left(\mathbf{e}_{1\tau}\right)_{-\infty\leq\tau\leq t}\right)}{\mathbf{var}\left(y_{i,t+h} \middle| \left(\mathbf{Y}_{\tau}\right)_{-\infty\leq\tau\leq t}\right)}$$

The $\mathbf{FVR}_{i,h}$ statistic measures the reduction in the forecast variance of variable i at horizon h induced by knowing the sequence of the identified sentiment shocks. Plagborg-Moller and Wolf (2019) show that the identified set for a scale parameter α (which is related to the absolute impulse response) is an interval with bounds that are more informative the stronger is the instrument. By imposing less restrictive assumptions, this FVR metric is robust to invertibility concerns that are inherent to proxy SVAR identification methods[9].

Figure 8 presents point estimates and 90 percent confidence bands of the FVR statistic. We find that the FVR for consumer confidence is around 20 percent for most forecast horizons apart from shorter ones where the sentiment shock explains up to 30 percent of the forecast variance of consumer confidence. For industrial production, the sentiment shock contributes very little at very short horizons but up to 20-25 percent at horizons between six months and one year. The shock accounts more significantly for fluctuations in unemployment, for which the FVR upper bound lies above 20 percent for forecast horizons from three to 16 months (peaking at 30 percent at the 10 months horizon). Thus, we find important contributions of the sentiment shock to business cycle variations in the real economy. Additional results, which are not presented here for economy of space, reveal that sentiment shocks also account for a large fraction of the fluctuations in vacancies and labor market tightness, peaking at 16 percent and 28 percent, respectively, at a 6-month horizon. The identified shock also explains at peak around 10 percent of the fluctuations in consumption of durables and non-durables.

By contrast, we find that the identified shock does not matter much for the nominal side of the economy, nor for asset prices or uncertainty. For the CPI, the FVR confidence bands include zero 10 months after the shock and point estimates never exceed 15 percent at any horizon. For real stock prices, the confidence bands include zero at all horizons and the point estimates never exceed 10 percent, and sentiment shocks explain very little of uncertainty fluctuations. The only nominal variable for which we do find some evidence of a more significant impact of sentiments is the short-term nominal interest rate where the upper bound hovers around 15 percent for

[9] In fact, the R_l^2 measure of invertibility proposed by Plagborg-Moller and Wolf (2019) indicates that invertibility may be an issue for low values of l but not for $l \geq 4$ months and that the estimated FVR upper bounds are "informative" after four months.

horizons beyond 5 months.

The significant contribution of sentiment shocks to macroeconomic fluctuations that we document is consistent with the findings in other papers such as Blanchard *et al.* (2013) and Levchenko and Pandalai-Nayar (2020) although the former of these finds a much larger contribution to consumption fluctuations at short forecast horizons while the latter finds a larger contribution to output fluctuations at short horizons than we do. These differences could be due to our use of higher frequency data or, more likely, to our different identification strategy. In contrast to these authors', we provide direct evidence rather than relying more indirectly on moments of the data. Regardless of these differences, each of these contributions agree on the fact that shocks unrelated to economic fundamentals appear to be an important source of impulses to the U.S. business cycle. We add to this the importance of sentiments for key labor market aggregates.

4 Theory

We study a heterogeneous agents model similar to Ravn and Sterk (2020) with uninsurable unemployment risk, rigid goods market prices and matching frictions in the labor market. This model generates an interaction between supply and demand which can lead, depending on key structural parameters, to multiple long-run equilibria. When there are multiple steady-states, temporary purely expectations-driven fluctuations can also exist. We consider sentiment shocks as causing shifts of agents' confidence between optimism and pessimism selecting the equilibrium towards which the economy is converging. We use the model to provide a structural interpretation of the empirical results.

4.A The Model

Preferences: A continuum of measure one of infinitely lived households indexed by $i \in [0, 1]$ maximizes expected discounted utility. Agents live in single-member households, consume a bundle of goods, $\mathbf{c}_i$, and face uninsurable unemployment risk. Preferences are given as:

$$\mathbf{U}_{i,s} = \mathbb{E}_s \sum_{h=0}^{\infty} \beta^h \left(\frac{\mathbf{c}_{i,s+h}^{1-\mu} - 1}{1-\mu} - \zeta \mathbf{n}_{i,s} \right) \tag{9}$$

$\mathbb{E}_s x_{s+h}$ denotes the expectation of x_{s+h} given date s information. $\mathbf{c}$ is a constant elasticity of substitution aggregate over individual goods' varieties:

$$\mathbf{c}_{i,s} = \left(\int_j \left(\mathbf{c}_{i,s}^j \right)^{1-1/\gamma} dj \right)^{1/(1-1/\gamma)} \tag{10}$$

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

$$\mathbf{n}_{i,s} = \begin{cases} 0 & \text{if not employed at date } s \\ 1 & \text{if employed at date } s \end{cases}$$

Employed agents earn a real wage $\mathbf{w}_s$ while those not employed receive an endowment $\vartheta > 0$.

Technology: There is a continuum of firms indexed by j each producing a differentiated good, $\mathbf{y}_j$, with a linear production function in labor:

$$\mathbf{y}_{j,s} = A\mathbf{n}_{j,s} \tag{11}$$

where $A > 0$ is a constant.

Firms hire labor in a matching market. At the end of each period, a fraction $\omega \in (0, 1)$ of existing worker-firm matches are dissolved. New hires are made by posting vacancies, $\mathbf{v}_j$, at the beginning of the period prior to production. Vacancies are filled at the rate $\mathbf{q}$ which firms take as given. The law of motion of firm j's employment is given as:

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

We assume that a measure of vacancies $\mathbf{v_F} \geq 0$ can be posted for free while each vacancy in excess of this measure, $\mathbf{v}_{j,s} - \mathbf{v_F}$, comes at the flow cost $\kappa > 0$ per vacancy, per period. Furthermore, we impose that:

$$\mathbf{v}_{j,s} \geq \mathbf{v_F},\ \forall j, s \tag{13}$$

The allowance for free vacancies captures the fact that some jobs may be filled through informal channels without the need for firms to engage in costly hiring efforts.

Matching market: New matches, $\mathbf{m}$, are determined by:

$$\mathbf{m}_s = \overline{m}\mathbf{e}_s^{\alpha}\mathbf{v}_s^{1-\alpha} \tag{14}$$

where $\mathbf{e}$ is the measure of non-employed workers who are participating in the labor market and looking for employment, and $\mathbf{v} = \int \mathbf{v}_j dj$ is the measure of aggregate vacancies. $\overline{m} > 0$ is a constant and $0 < \alpha < 1$ denotes the elasticity of matches to the measure of searchers.

Let $\theta = \mathbf{v}/\mathbf{e}$ denote labor market tightness. The job finding rate, $\eta_s \in [0, 1]$, and the vacancy filling rate are then given as:

$$\eta_s = \overline{m}\theta_s^{1-\alpha} \tag{15}$$

$$\mathbf{q}_s = \overline{m}\theta_s^{-\alpha} = \overline{m}^{1/(1-\alpha)}\eta_s^{-\alpha/(1-\alpha)} \tag{16}$$

Prices and Wages: Firms are monopolistically competitive and set the nominal price of their product, $\mathbf{P}_j$, subject to quadratic price adjustment costs. They maximize the objective function:

$$\mathbf{\Phi}_{j,s} = \mathbb{E}_s \sum_{h=0}^{\infty} \mathbf{\Lambda}_{j,s,s+h} \left[\frac{\mathbf{P}_{j,s+h}}{\mathbf{P}_{s+h}} \mathbf{y}_{j,s+h} - \mathbf{w}_{s+h}\mathbf{n}_{j,s+h} - \kappa \left(\mathbf{v}_{j,s+h} - \mathbf{v}_{\mathbf{F}} \right) - \frac{\phi}{2} \left(\frac{\mathbf{P}_{j,s+h}}{\mathbf{P}_{j,s+h-1}} - 1 \right)^2 \mathbf{y}_{s+h} \right] \tag{17}$$

where $\mathbf{\Lambda}_{j,s,s+h}$ denotes the stochastic discount factor of the owners of the firms, and $\mathbf{P}$ is the aggregate price level. $\phi \geq 0$ quantifies price adjustment costs, and $\mathbf{y} = \int \mathbf{y}_j dj$ is aggregate output. Firms maximize (17) subject to (11), (12), (13) and:

$$\mathbf{y}_{j,s} = \left(\frac{\mathbf{P}_{j,s}}{\mathbf{P}_s} \right)^{-\gamma} \mathbf{y}_s \tag{18}$$

where the latter follows as the solution to the households cost minimization problem.

We assume that the real wage is determined as:

$$\mathbf{w}_s = \overline{w} \left(\frac{\eta_s}{\overline{\eta}} \right)^{\chi} \tag{19}$$

where $\overline{w}$,$\overline{\eta} > 0$ are constants. This specification assumes that real wages respond to changes in the job finding rate with an elasticity of $\chi \geq 0$.

Asset and Budget Constraints: Firms are owned by a small share ξ of the agents that we will refer to as capitalists. These agents hold equity portfolios but no bonds, and are assumed not to participate in the labor market. The remaining share of households, $1 - \xi$, only have access to the bond markets.[10]

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

$$\mathbf{c}_{i,s} + \mathbf{x}_{i,s} \leq \vartheta + \frac{\mathbf{R}_{x,s}}{\mathbf{\Pi}_s} \mathbf{x}_{i,s-1} \tag{20}$$

and we assume that they cannot go short on equity:

$$\mathbf{x}_{i,s} \geq 0 \tag{21}$$

Workers face a sequence of budget constraints:

$$\mathbf{c}_{i,s} + \mathbf{b}_{i,s} \leq \mathbf{w}_s \mathbf{n}_{i,s} + \vartheta \left(1 - \mathbf{n}_{i,s} \right) + \frac{\mathbf{R}_{s-1}}{\mathbf{\Pi}_s} \mathbf{b}_{i,s-1} \tag{22}$$

[10]These assumptions can be micro-founded assuming limited participation in equity markets and the borrowing constraint (23), see Ravn and Sterk (2020).

and the borrowing constraint:

$$\mathbf{b}_{i,s} \geq -\varkappa \mathbf{w}_s \mathbf{n}_{i,s} \tag{23}$$

Monetary Policy: The central bank sets the nominal interest rate as:

$$\mathbf{R}_s = \overline{R} \left(\frac{\mathbf{\Pi}_s}{\overline{\Pi}} \right)^{\delta_\Pi}, \ \bar{R} \geq 1 \tag{24}$$

where $\overline{\Pi}$ is an inflation target, $\overline{R}$ is a constant, and δ_Π determines the response of the nominal interest rate to deviations of inflation from its target.

Equilibrium: The model displays limited heterogeneity in equilibrium. Capitalists do not participate in the labor market and, hence, face no idiosyncratic risk. It follows that firms have identical discount factors; Unemployed workers would like to borrow but are prevented from doing so due to the borrowing constraint, implying that they will not be on their Euler equation; Employed workers have an incentive to save due to unemployment risk and therefore are on their Euler equation (since the borrowing constraint does not prevent saving). Hence, there are only three types of agents in equilibrium with no within-group inequality but potentially substantial across-groups disparities.

We focus on a symmetric equilibrium where the firms all set the same prices and make the same vacancy posting and employment decisions. The equilibrium conditions are given by:

$$\mathbf{w}_s^{-\mu} = \beta \mathbb{E}_s \frac{\mathbf{R}_s}{\mathbf{\Pi}_{s+1}} \mathbf{w}_{s+1}^{-\mu} \left[1 + \omega \left(1 - \eta_{s+1}\right) \left(\left(\vartheta / \mathbf{w}_{s+1} \right)^{-\mu} - 1 \right) \right], \tag{25}$$

$$1 - \gamma + \gamma \mathbf{mc}_s = \phi \left(\mathbf{\Pi}_s - 1 \right) \mathbf{\Pi}_s - \phi \beta \mathbb{E}_s \left(\frac{\mathbf{c}_{c,s+1}}{\mathbf{c}_{c,s}} \right)^{-\mu} \left(\mathbf{\Pi}_{s+1} - 1 \right) \mathbf{\Pi}_{s+1} \frac{\mathbf{y}_{s+1}}{\mathbf{y}_s} \tag{26}$$

$$\mathbf{mc}_s = \frac{1}{A} \left(\mathbf{w}_s + \frac{\kappa}{\mathbf{q}_s} - \lambda_{v,s} - (1 - \omega) \beta \mathbb{E}_s \left(\frac{\mathbf{c}_{c,s+1}}{\mathbf{c}_{c,s}} \right)^{-\mu} \left\{ \frac{\kappa}{\mathbf{q}_{s+1}} - \lambda_{v,s+1} \right\} \right) \tag{27}$$

$$\mathbf{c}_{c,s} = \frac{1}{\xi} \left(\mathbf{y}_s - \kappa \left(\mathbf{v}_s - v_{\mathbf{F}} \right) - \mathbf{w}_s \mathbf{n}_s - \frac{\phi}{2} \left(\mathbf{\Pi}_s - 1 \right)^2 \mathbf{y}_s \right) + \vartheta \tag{28}$$

$$\mathbf{n}_s = (1 - \omega)(1 - \eta_s) \mathbf{n}_{s-1} + \eta_s (1 - \xi) \tag{29}$$

in addition to (11), (12), (13), (15), (16), (19), and (24).

Equation (25) is the Euler equation for the employed workers. In equilibrium, while these agents are not borrowing constrained, they consume their income period-by-period due to asset market clearing. The left hand side of (25) is the marginal utility of consumption of a currently employed worker. The right hand side is the discounted expected real return on bonds, $\beta \mathbb{E}_s \mathbf{R}_s / \mathbf{\Pi}_{s+1}$, times expected marginal utility next period; The latter is the convex combination of marginal utility if employed, $\mathbf{w}_{s+1}^{-\mu}$, and when unemployed, $\vartheta^{-\mu}$, with the weights being equal to the probabilities of these two states next period, conditional upon being employed today. The probability of job loss at the end of the period is ω and the probability of finding a new job at the beginning of the subsequent period is η_{s+1}. Hence, currently employed workers face unemployment next period with probability, $\omega(1-\eta_{s+1})$. Due to the lack of unemployment insurance, employed workers increase their desired (precautionary) savings when $\omega(1-\eta_{s+1})$ rises or when the income loss associated with job loss, w_{s+1}/ϑ rises. The former moves countercyclically as the job finding rate declines in recessions while the latter is procyclical. Hence, precautionary savings may exert an upward or downward pressure on real interest rates in recessions depending on whether unemployment or earnings risk dominates. When this risk is countercyclical the demand and supply sides of the economy reinforce jointly the impact of shocks (see Ravn and Sterk (2020)). Conversely, when real wage adjustments dominate, earning risk is procyclical (households save for precautionary reasons in booms) which has stabilizing effects.

The expression in (26) is the optimal price setting condition for the monopolistic producers where we have imposed symmetry. This condition determines inflation as an increasing function of current and (discounted) expected future real marginal costs, $\mathbf{mc}_s$. Equation (27), in turn, determines real marginal costs. In this expression, $\lambda_{v,s} \geq 0$, is the Kuhn-Tucker multiplier on (13) which satisfies the condition:

$$\lambda_{v,s}(\mathbf{v}_{j,s}-\mathbf{v_F})=0 \tag{30}$$

When $\mathbf{v}_{j,s} > \mathbf{v_F}$, real marginal costs are determined by the real wage and by effective hiring costs, $\frac{\kappa}{\mathbf{q}_s}-(1-\omega)\beta\mathbb{E}_s\left(\frac{\mathbf{c}_{c,s+1}}{\mathbf{c}_{c,s}}\right)^{-\mu}\frac{\kappa}{\mathbf{q}_{s+1}}$, relative to productivity, A. The cost of hiring depends on κ, the vacancy posting cost, and inversely on the vacancy filling rate, $\mathbf{q}_s$. When $\mathbf{v}_{j,s} = \mathbf{v_F}$, the Kuhn-Tucker condition induces the shadow cost, $\lambda_{v,s}$.

Equation (28) defines the capitalists' consumption, $\mathbf{c}_{c,s}$, which enters the stochastic discount factors in (26) – (27), as output net of labor, vacancy posting, and price adjustment costs (plus home production). Finally, (29) is the law of motion of employment.

Sentimental Business Cycles

We now wish to explore how this model can lead to sentiment driven fluctuations in the economy which – on the households side – originate from doubts about employment prospects and – on the firms side – about demand conditions.

Permanent unemployment traps: The deterministic steady-states of the model are determined as the stationary solutions of the equilibrium conditions listed earlier. Note, however, that due to labor turnover, while aggregate variables are constant over time in the deterministic steady-state, these equilibria display idiosyncratic uncertainty. Letting "ss" denote a variable in a steady-state, the stationary equilibria of the economy can be derived from:

$$
\begin{aligned}
1 &= \beta \frac{\overline{R}}{\overline{\Pi}^{\delta_\Pi}} \mathbf{\Pi}_{ss}^{\delta_\Pi - 1} \left[1 + \omega \left(1 - \eta_{ss}\right) \left(\left(\frac{\vartheta}{\mathbf{w}_{ss}} \right)^{-\mu} - 1 \right) \right], && (31) \\
\mathbf{mc}_{ss} &= \frac{\gamma - 1}{\gamma} + \frac{\phi}{\gamma} \left(1 - \beta\right) \left(\mathbf{\Pi}_{ss} - 1\right) \mathbf{\Pi}_{ss} && (32) \\
\mathbf{mc}_{ss} &= \frac{1}{A} \left(\mathbf{w}_{ss} + \left(1 - \left(1 - \omega\right) \beta\right) \left(\frac{\kappa}{\mathbf{q}_{ss}} - \lambda_{v,ss} \right) \right) && (33) \\
\mathbf{w}_{ss} &= \overline{w} \left(\frac{\eta_{ss}}{\overline{\eta}} \right)^{\chi} && (34) \\
\mathbf{q}_{ss} &= \overline{m} \left(\frac{\eta_{ss}}{\overline{m}} \right)^{-\alpha/(1-\alpha)} && (35) \\
\mathbf{n}_{ss} &= \frac{\eta_{ss} \left(1 - \xi\right)}{1 - \left(1 - \omega\right) \left(1 - \eta_{ss}\right)} && (36) \\
0 &= \lambda_{v,ss} \left(\mathbf{v}_{ss} - \mathbf{v}_{\mathbf{F}} \right) && (37)
\end{aligned}
$$

and the remaining variables are determined as functions of these variables.

Substituting away for marginal costs, real wages, and the vacancy yield, the first five of these conditions can be summarized by two conditions, $\Pi^{EE}(\eta)$ and $\Pi^{PC}(\eta)$:

$$
\begin{aligned}
1 &= \beta \overline{R} \left(\frac{\Pi_{\mathbf{ss}}}{\overline{\Pi}} \right)^{\delta_\Pi} \frac{1}{\Pi_{\mathbf{ss}}} \left[1 + \omega \left(1 - \eta_{\mathbf{ss}}\right) \left(\left(\frac{\vartheta}{\overline{w} \left(\frac{\eta_{\mathbf{ss}}}{\overline{\eta}} \right)^{\chi}} \right)^{-\mu} - 1 \right) \right] && (38) \\
\left(1 - \phi\beta\right) \left(\Pi_{\mathbf{ss}} - 1\right) \Pi_{\mathbf{ss}} &= 1 - \gamma + \frac{\gamma}{A} \left(\overline{w} \left(\frac{\eta_{\mathbf{ss}}}{\overline{\eta}} \right)^{\chi} + \left(\kappa \bar{m} \left(\frac{\eta_{\mathbf{ss}}}{\overline{m}} \right)^{-\alpha/(1-\alpha)} - \lambda_{v,ss} \right) \left(1 - \left(1 - \omega\right) \beta\right) \right) && (39)
\end{aligned}
$$

Since marginal costs are increasing in real wages and decreasing in the vacancy filling rate, $\Pi^{PC}(\eta)$ from equation (39) is positively sloped (as long as $\Pi > 1/2$). This reflects that firms charge higher prices when marginal costs rise due to workers being harder to hire and costlier to employ. The slope of $\Pi^{EE}(\eta)$ instead depends on δ_Π and on the $\partial\Theta/\partial\eta_{\mathbf{ss}}$, where $\mathbf{\Theta}_{ss} = 1 + \omega\left(1 - \eta_{ss}\right) \left(\left(\frac{\vartheta}{\mathbf{w}_{ss}} \right)^{-\mu} - 1 \right)$. We impose that the intended steady-state (defined below) displays local determinacy and a necessary (but not sufficient) condition for this is that $\delta_\Pi > 1/\beta$. In this case, the sign of the slope of $\Pi^{EE}(\eta)$ is determined by $\partial\Theta/\partial\eta_{\mathbf{ss}}$.

If real wages are very elastic, $\partial\Theta/\partial\eta_{\mathbf{ss}} > 0$, this relationship will be negatively sloped, $\partial\Pi^{EE}(\eta)/\partial\eta < 0$, and the model has a unique stationary equilibrium, the *intended steady-state* (indicated by $\mathbf{I}$) where $\lambda_{v,\mathbf{I}} = 0$ and $\mathbf{v}_{\mathbf{I}} > \mathbf{v}_{\mathbf{F}}$.

However, if $\partial\mathbf{\Theta}/\partial\eta < \left(\partial\mathbf{\Theta}/\partial\eta\right)_{crit} < 0$, an additional steady-state may arise which Ravn and Sterk (2020) refer to as an "unemployment trap" (indicated by $\mathbf{u}$). This steady state features high unemployment and low inflation and arises because, under sufficiently strong countercyclicality of earnings risk, expectations of weak labor demand and weak goods demand can reinforce each other to the point that firms stop hiring. In this stationary equilibrium, $\lambda_{\mathbf{u},v} > 0$ and $\mathbf{v_u} = \mathbf{v_F}$ which implies that:

$$
\begin{aligned}
\mathbf{n_u} &= \frac{(\mathbf{1}-\xi)\,\eta_{\mathbf{u}}}{\mathbf{1}-(\mathbf{1}-\omega)(\mathbf{1}-\eta_{\mathbf{u}})} < \mathbf{n_I} \\
\eta_{\mathbf{u}} &= \overline{m}\left(\frac{\mathbf{v_F}}{\mathbf{1}-\xi-(\mathbf{1}-\omega)\,\mathbf{n_u}}\right)^{1-\alpha} < \eta_{\mathbf{I}} \\
\mathbf{w_u} &= \overline{w}\left(\frac{\eta_{\mathbf{u}}}{\overline{\eta}}\right)^{\chi} < \overline{\mathbf{w}}_I \\
\Pi_{\mathbf{u}} &= \left[\beta\frac{\overline{R}}{\overline{\Pi}^{\delta_\Pi}}\left(1+\omega(1-\eta_u)\left(\left(\frac{\vartheta}{\mathbf{w}_u}\right)^{-\mu}-1\right)\right)\right]^{1/(1-\delta_\Pi)} < \mathbf{\Pi_I}
\end{aligned}
$$

Although the existence of this steady-state does not depend on $\mathbf{v_F} > 0$, the presence of free vacancies implies that the unemployment trap rate is below unity. When $\partial\mathbf{\Theta}/\partial\eta < (\partial\mathbf{\Theta}/\partial\eta)_{crit} < 0$, it follows that $\partial\Pi^{EE}(\eta)/\partial\eta > \partial\Pi^{PC}(\eta)/\partial\eta$, that translates into the condition:

$$
\left(\left(\frac{\vartheta}{\mathbf{w_{ss}}}\right)^{-\mu}-1\right) > \mu\chi\frac{(1-\eta_{ss})}{\eta_{ss}}\left(\frac{\vartheta}{\mathbf{w_{ss}}}\right)^{-\mu}
$$

which is more likely to hold the less elastic are wages to the job finding rate and the larger is the loss in income when a worker suffers job loss. However, due to possible non-monotonicities, the slope condition is only necessary. Sufficiency for existence hinges on whether $\lim_{\eta\to\eta_{\mathrm{u}}}\Pi^{EE}(\eta) < \lim_{\eta\to\eta_{\mathrm{u}}}\Pi^{PC}(\eta)$.

Sentiment Driven Business Cycles: When the unemployment trap steady-state exists, there may also be temporary episodes where the equilibrium diverges from the intended steady-state. We will consider stochastic sunspot equilibria where the economy fluctuates between equilibria in the vicinities of the intended steady-state and of the unemployment trap. We model a negative sentiment shocks as inducing a wave of pessimism where employed agents increase their desired savings due to doubts about future employment prospects; firms reduce vacancies postings due to doubts about goods demand; and these negative beliefs reinforce each other to such an extent that the vacancy boundary condition becomes binding. As a result pessimistic beliefs temporarily take the economy on a path towards a low-activity cum high-unemployment outcome until agents turn optimistic and the economy returns to a path towards a high activity/low unemployment equilibrium. Such fluctuations will be our notion of sentimental business cycles.

Let ψ denote sentiments and assume that it follows a discrete two-state homogeneous Markov chain fluctuating between optimism, $\psi_s = \psi^o$, and pessimism, $\psi_s = \psi^p$, with transition probability matrix $\mathbf{\Upsilon}^{\psi}$. We denote the transition probabilities by $p^{\psi}_{ij} = \Pr(\psi = \psi^i | \psi_{-1} = \psi^j) \in [0,1]$ for $j \in (o,p)$ where $\sum_i p^{\psi}_{ij} = 1$. For simplicity we assume that there are no other shocks to the economy.

We solve for the decision rules that satisfy the equilibrium conditions listed earlier, by extending the state variables with the sunspot indicator:

$$\mathbf{n}_s = g_z\left(\mathbf{n}_{s-1,}\psi_s\right), \ \mathbf{n}_{s-1,} \text{ given} \tag{40}$$

$$\mathbf{h}_s = g_h\left(\mathbf{n}_{s,}\psi_s\right) \tag{41}$$

where $\mathbf{h}_s = [\mathbf{\Pi}_s, \mathbf{R}_s, \eta_s, \mathbf{w}_s, \mathbf{mc}_s, \mathbf{c}_{c,s}, \mathbf{v}_s, \lambda_{v,s}]'$. When the equilibrium is unique, the sunspot is a redundant state variable and the economy converges to the intended steady-state from the initial employment level regardless of ψ. When the unemployment trap instead exists, the sunspot selects the equilibrium towards which the economy converges.

When agents are pessimistic, firms stop posting costly vacancies, $\lambda_{v,p}(\mathbf{n}) > 0$ and $\mathbf{v}_p(\mathbf{n}) = \mathbf{v_F}$. As long as agents remain pessimistic, the economy converges to a pessimistic sunspot limit where $\left(\mathbf{n}_p^l, \eta_p^l, \mathbf{w}_p^l, \Theta_p^l, \mathbf{v}_p^l\right) = (\mathbf{n_u}, \eta_\mathbf{u}, \mathbf{w_u}, \Theta_\mathbf{u}, \mathbf{v_F})$ while $\left(\mathbf{mc}_p^l, \mathbf{\Pi}_p^l, \mathbf{c}_{c,p}^l, \lambda_p^l\right)$ are the solutions to the following system of equations:

$$\begin{aligned}
\left(\mathbf{w}_p^l\right)^{-\mu} &= \beta\overline{R}\left(\mathbf{\Pi}_p^l\right)^{\delta_\pi-1}\left(\mathbf{w}_p^l\right)^{-\mu}\Theta_p^l\left(p_{pp}^{\psi} + (1-\varphi_{pp})\left(\frac{\mathbf{\Pi}_o\left(\mathbf{n}_p^l\right)}{\mathbf{\Pi}_p^l}\right)^{\delta_\pi-1}\left(\frac{\mathbf{w}_o\left(\mathbf{n}_p^l\right)}{\mathbf{w}_p^l}\right)^{-\mu}\frac{\Theta_o\left(\mathbf{n}_p^l\right)}{\Theta_p^l}\right)\\
\gamma\mathbf{mc}_p^l &= (\gamma-1) + \phi\left(1-\beta p_{pp}^{\psi}\right)\left(\mathbf{\Pi}_p^l - 1\right)\mathbf{\Pi}_p^l\\
&\quad -\phi\beta\left(1-p_{pp}^{\psi}\right)\left(\frac{\mathbf{c}_{c,o}\left(\mathbf{n}_p^l\right)}{\mathbf{c}_{c,p}^l}\right)^{-\mu}\left(\mathbf{\Pi}_o\left(\mathbf{n}_p^l\right)-1\right)\mathbf{\Pi}_o\left(\mathbf{n}_p^l\right)\frac{n_o\left(\mathbf{n}_p^l\right)}{\mathbf{n}_p^l}\\
\mathbf{mc}_p^l &= \frac{1}{A}\left(\mathbf{w}_p^l + \left(1-p_{pp}^{\psi}(1-\omega)\beta\right)\left(\frac{\kappa}{\mathbf{q}_p^l}-\lambda_p^l\right) - \left(1-p_{pp}^{\psi}\right)(1-\omega)\beta\left(\frac{\mathbf{c}_{c,o}\left(\mathbf{n}_p^l\right)}{\mathbf{c}_{c,p}^l}\right)^{-\mu}\frac{\kappa}{q_o\left(\mathbf{n}_p^l\right)}\right)\\
\mathbf{c}_{c,p}^l &= \frac{A}{\xi}\left(1-\mathbf{w}_p^l - \frac{\phi}{2}\left(\mathbf{\Pi}_p^l-1\right)^2\right)\mathbf{n}_p^l + \vartheta
\end{aligned}$$

where $\mathbf{q}_p^l = \overline{m}^{1/(1-\alpha)}\left(\eta_p^l\right)^{-\alpha/(1-\alpha)}$ and $\Theta_p^l = \left[1+\omega\left(1-\eta_p^l\right)\left(\left(\vartheta/w_p^l\right)^{-\mu}-1\right)\right]$. In these expressions $x_o\left(\mathbf{n}_p^l\right)$ denotes the decision rule for variable x should agents become optimistic given the current employment level, $\mathbf{n}_p^l$.

The level of employment and wages, the job finding and vacancy filling rates in the pessimistic sunspot limit, thus, correspond to their solutions in the unemployment trap *steady-state*. The reason for this is that while agents hold pessimistic beliefs, firms do not post any costly vacancies, $\mathbf{v}_p^l = \mathbf{v_F}$, and the employment dynamics are therefore given by:

$$\begin{aligned}
\mathbf{n}_p &= (1-\omega)\left(1-\eta_p\left(\mathbf{n}_{-1}\right)\right)\mathbf{n}_{-1} + \eta_p\left(\mathbf{n}_{-1}\right)(1-\xi)\\
\eta_p\left(\mathbf{n}_{-1}\right) &= \overline{m}\left(\frac{\mathbf{v_F}}{\mathbf{1}-\xi-(\mathbf{1}-\omega)\,\mathbf{n_{-1}}}\right)^{1-\alpha}
\end{aligned}$$

The employment level in the pessimistic sunspot limit is the fixed point of this mapping which yields a solution identical to the unemployment trap steady state. Since the job finding rate in the pessimistic sunspot limit is a function of the employment level only, and wages are determined by the job finding rate, it follows that the job market outcomes in the pessimistic sunspot limit are identical to those in the unemployment trap steady-state. It follows that, conditional upon existence of the pessimistic sunspot, monetary policy is unable to impact on the labor market outcomes as long as agents remain pessimistic. Inflation, marginal costs, entrepreneurial consumption and the shadow cost of the lower bound on vacancies, instead, do respond to monetary policy because they are influenced by the policy functions that hold should the wave of pessimism turn to optimism.

When agents are optimistic, $\lambda_{v,o} = 0$ and $\mathbf{v}_{s,o} > \mathbf{v_F}$, and the decision rules solve the following system of equations:

$$
\begin{aligned}
\left(\mathbf{w}_o\left(\mathbf{n_{-1}}\right)\right)^{-\mu} &= \beta\overline{R}\left(\mathbf{\Pi}_o\left(\mathbf{n_o}\right)\right)^{\delta_\pi-1}\left(\mathbf{w}_o\left(\mathbf{n_o}\right)\right)^{-\mu}\Theta_o\left(\mathbf{n_o}\right) \\
&\quad\times\left(p_{oo}^{\psi}+\left(1-p_{oo}^{\psi}\right)\left(\frac{\mathbf{\Pi}_p\left(\mathbf{n_p}\right)}{\mathbf{\Pi}_o\left(\mathbf{n_o}\right)}\right)^{\delta_\pi-1}\left(\frac{\mathbf{w}_p\left(\mathbf{n_p}\right)}{\mathbf{w}_o\left(\mathbf{n_o}\right)}\right)^{-\mu}\frac{\Theta_p\left(\mathbf{n_p}\right)}{\Theta_o\left(\mathbf{n_o}\right)}\right) \\
\gamma\mathbf{mc}_o\left(\mathbf{n_{-1}}\right) &= \left(\gamma-1\right)+\phi\left(\mathbf{\Pi}_o\left(\mathbf{n_{-1}}\right)-1\right)\mathbf{\Pi}_o\left(\mathbf{n_{-1}}\right)-\phi\beta p_{oo}^{\psi}\left(\mathbf{\Pi}_o\left(\mathbf{n_o}\right)-1\right)\mathbf{\Pi}_o\left(\mathbf{n_o}\right)\left(\frac{\mathbf{c}_{c,o}\left(\mathbf{n_o}\right)}{\mathbf{c}_{c,o}\left(\mathbf{n_{-1}}\right)}\right)^{-\mu}\frac{\mathbf{n_o}}{\mathbf{n}_{-1}} \\
&\quad-(1-p_{oo}^{\psi})\phi\beta\left[\left(\frac{\mathbf{c}_{c,p}\left(\mathbf{n_p}\right)}{\mathbf{c}_{c,o}\left(\mathbf{n_{-1}}\right)}\right)^{-\mu}\left(\mathbf{\Pi}_p\left(\mathbf{n_p}\right)-1\right)\mathbf{\Pi}_p\left(\mathbf{n_p}\right)\frac{\mathbf{n_p}}{\mathbf{n}_{-1}}\right] \\
\mathbf{mc}_o\left(\mathbf{n_{-1}}\right) &= \frac{1}{A}\left(\mathbf{w}_o\left(\mathbf{n_{-1}}\right)+\frac{\kappa}{\mathbf{q}_o\left(\mathbf{n_{-1}}\right)}-p_{oo}^{\psi}(1-\omega)\beta\left(\frac{\mathbf{c}_{c,o}\left(\mathbf{n}_o\right)}{\mathbf{c}_{c,o}\left(\mathbf{n_{-1}}\right)}\right)^{-\mu}\frac{\kappa}{\mathbf{q}_o\left(\mathbf{n}_o\right)}\right) \\
&\quad-\frac{1}{A}\left(1-p_{oo}^{\psi}\right)\left(1-\omega\right)\beta\left(\frac{\mathbf{c}_{c,p}\left(\mathbf{n}_p\right)}{\mathbf{c}_{c,o}\left(\mathbf{n_{-1}}\right)}\right)^{-\mu}\left(\frac{\kappa}{\mathbf{q}_p\left(\mathbf{n}_p\right)}-\lambda_{v,p}\left(\mathbf{n}_p\right)\right) \\
\mathbf{c}_{c,o}\left(\mathbf{n}\right) &= \frac{A}{\xi}\left(1-\frac{\kappa}{\mathbf{n}}\left(\mathbf{v}_o-\mathbf{v_F}\right)-\mathbf{w}_o-\frac{\phi}{2}\left(\Pi_o-1\right)^2\right)\mathbf{n}_o+\vartheta \\
\mathbf{n_j} &= \left(1-\omega\right)\mathbf{n}_{-1}+\mathbf{q}_j\mathbf{v}_j, j=o,p
\end{aligned}
$$

where $\Theta_o = \left[1+\omega\left(1-\eta_o\right)\left(\left(\vartheta/w_o\right)^{-\mu}-1\right)\right]$ and $\mathbf{q}_j = \bar{m}\left(\frac{\eta_j}{\bar{m}}\right)^{-\alpha/(1-\alpha)}$. One feature of this solution is that if $p_{oo}^{\psi} < 1$, the optimistic sunspot limit will be different from the intended steady-state due to the risk of agents losing confidence.

Calibration: Our calibration exercise is summarized in Table 2. One period corresponds to a month. We assume an annual real interest rate of 3.5 percent and set the steady-state gross inflation equal to 4.5 percent. These values are close to what was observed in the U.S. in the sample period considered in the empirical section of the paper. We set the degree of risk aversion to $\mu = 2$, a standard value in the literature. Consumption is assumed to fall by 15 percent of the intended steady-state wage upon job loss and we calibrate accordingly $\vartheta = 0.85\mathbf{w_I}$. This value is in the range of values of empirical estimates. Hurd and Rohwedder (2016) and Chodorow-Reich and Karabarbounis (2016) find that consumption drops by 12 percent and 20 percent, respectively, upon job loss.

We set the elasticity of substitution between intermediate goods equal to 8, which implies a mark-up close to 12 percent in the steady-state. The value of ϕ determines the degree of nominal rigidities. One can relate this to the average price contract length by exploiting the relationship between the log-linearized NK Phillips curve in the Calvo model and the one implied by the Rotemberg model. The slope of the Phillips curve with respect to real marginal costs equals to γ/ϕ, while the corresponding value in the Calvo model is $(1-\varpi)(1-\varpi\beta)/\varpi$, where $\zeta = 1/(1-\varpi)$ is the average contract length. Exploiting this relationship we calibrate ϕ so that the average contract length is 10 months.

The elasticity of the matching function with respect to unemployment, α, is set to 60 percent and the monthly job separation rate, ω, is calibrated to 3.5 percent per month. Next, we assume that the vacancy cost parameter, κ, is consistent with an average hiring cost of 4.4 percent of the quarterly wage bill. This is in line with the estimates of Silva and Toledo (2009) who report that hiring costs are somewhere between 4 and 7 percent of the quarterly wage bill for new hires in the U.S.

We assume that wages are rigid and set the wage elasticity parameter, $\chi = 0.001$. Any direct attempt at estimating this parameter yields very low estimates because real wages move little at the monthly frequency relative to the job finding rate. In our analysis, this elasticity matters mainly for the existence of the unemployment trap while the dynamics are insensitive to its value. We normalize average productivity to one and set the share of entrepreneurs in the total population to one percent. The inflation coefficient in the Taylor rule equals 1.5, a conventional value in the literature.

Next we assume that the steady-state unemployment rate equals 5 percent in the intended steady state. This implies that the monthly job finding rate, $\eta_{\mathbf{I}}$, is equal to 39.9 percent so that the average unemployment duration upon job loss is around 2.5 months. We calibrate the match efficiency parameter, $\overline{\mathbf{m}}$, to target a monthly vacancy filling rate in the intended steady-state of 0.23, which is consistent with the value assumed by e.g. Ravenna and Walsh (2008).

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

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

which implies at the annual frequency that $\beta^{12} = 0.88$. The relatively low value of β derives from the precautionary savings motive.

The calibration of the unemployment rate in the unemployment trap is informed by historical evidence on U.S. unemployment. Prior to Covid-19, the U.S. civilian unemployment rate has rarely exceeded 9 percent (apart from the early 1980s and in the Great Recession when unemployment went above 10 percent but only for short periods of time). We therefore assume that the unemployment rate in the unemployment trap steady-state is 9 percent but also examine robustness to this assumption. Should this level of unemployment be attained, the job finding rate declines to 26.1 percent implying an increase in the expected average duration of unemployment to 4 months approximately.

From the calibration of the unemployment trap, it follows that 50.7 percent of vacancies are filled in the informal market when the economy is in the intended steady-state. This value is in the range of empirical estimates for the U.S. Galeotti and Merlino (2014), for example, report that between 30% to 50% of jobs are filled through the use of social networks, while Davis *et al.* (2013) find that 41.6 percent of hires occur in establishments with no vacancies.

We assume that the intended steady-state is absorbing, $\mathbf{p}_{oo}^{\psi} = 1$, while the persistence of pessimism is calibrated to $\mathbf{p}_{pp}^{\psi} = 0.85$. This implies that when agents turn pessimistic, this state will last on average for 6.7 months which is consistent with the persistence of the drop in the consumer confidence index that we estimated earlier.[11]

We obtain the equilibrium paths from numerical approximations of the functions in (40)-(41). We use a global solver given that the economy may drift far away from the intended equilibrium when agents turn pessimistic. We solve by time iteration using an endogenous grid method assuming piecewise linear policy functions on a grid for employment, $\mathbf{n}$, of 200 points.

A Sentimental Unemployment Trap: To see why the unemployment trap permits short-run dynamics driven by pessimism, Figure 9 plots $\Pi^{EE}(\eta)$ and $\Pi^{PC}(\eta)$ when using the calibrated parameter values.

The $\Pi^{PC}(\eta)$-schedule (indicated by PC) is upward sloping as discussed earlier, because real wages and hiring costs are increasing in the job finding rate. When $\mathbf{v}_s = \mathbf{v_F}$, the PC curve becomes vertical. The $\Pi^{EE}(\eta)$ schedule is also upward sloping. In our calibration $\mathbf{\Theta_I} = 1.0081$ and $\partial\mathbf{\Theta_I}/\partial\eta_\mathbf{I} = 0.38$ indicating that earnings risk is countercyclical. The countercyclicality is strong enough that $\partial\Pi^{EE}(\eta)/\partial\eta > \partial\Pi^{PC}(\eta)/\partial\eta$, so that the unemployment trap exists. In this steady state annualized inflation is 0.1 percent.

Dynamics in response to Sentiment Shocks: In Figure 10 we illustrate the dynamics of the economy during a sentimental business cycles. The results correspond to the average outcomes of 2000 simulations of the model where in each of them we start the economy out in the intended steady-state and then assume that agents at time 0 become pessimistic. We then simulate the Markov chain using the transition probability matrix Υ^{ψ}so that the duration of pessimism is stochastic in each simulation. The large number of replications imply that we derive approximations of the average path of the economy which emulate the impulse response functions estimated in the data.

The predominance of pessimism depresses economic activity. As pessimism sets in, output declines gradually reaching a maximum fall of 1.6 percent relative to the intended steady-state

[11]We have also solved the model assuming $\mathbf{p}_{oo}^{\psi} < 1$ and results are similar.

after approximately three months. Parallel to the drop in output is lower consumption with dynamics very similar to those of output (apart from an increase in the first periods which is an artifact of the Rotemberg price adjustment mechanism whereby the fall in inflation brings about more resources initially).

The impact of the pessimistic expectations is particularly clear on the labor market where unemployment surges and vacancies and labor market tightness drop suddenly. As long as agents are pessimistic, firms stop posting costly vacancies, $\mathbf{v}_p = \mathbf{v_F}$, and the recovery of vacancies depicted in Figure 10 therefore reflects the duration of pessimistic beliefs according to the Markov chain. The increase in unemployment peaks at three-four months after the prevalence of pessimism and after a year most of the increase in joblessness has disappeared with unemployment returning to the vicinity of its intended steady-state value. Notice that, due to the partial downward adjustment of employment, unemployment will almost never reach its pessimistic sunspot limit.

Hence, the recession that is produced by the sunspot when agents become pessimistic is very pronounced in the labor market. It derives from agents' pessimistic beliefs about adverse labor market outcomes being confirmed by firms cutting back on hiring which in turn lead to an increase in income risk faced by the employed agents when the earnings wedge is countercyclical. This is also reflected in the response of the wedge shown in Figure 10 which increases quite significantly upon impact and throughout the episode.

Recall that while the labor market outcomes (and gross output) in the pessimistic sunspot limit equal their values in the unemployment trap, inflation does not because agents at any point may turn optimistic. The inflation rate in the pessimistic sunspot limit is 2.2 percent annually which is much higher than in the unemployment trap steady-state. This moderate fall in inflation squares well with the lack of a strong impact of sentiment shocks on inflation that we observed in the data. Along the average sunspot path, the model implies a drop in inflation from its intended steady-state value of 4.5 percent annually to 2.4 percent, while the short term nominal interest rate falls from eight percent on annual basis to just below five percent. These monetary responses are still more pronounced than the empirical estimates but we will show below that shorter duration of pessimism can address this divergence.

In summary, the dynamics of the economy in response to a sunspot share many aspects of the empirical estimates of sentiment shocks. In particular, the labor market plays a central role with large and persistent responses of unemployment.

Sensitivity Analysis

Pessimism persistence: To examine sensitivity of the results, we first study how persistence of pessimism impacts on the dynamics of a sentimental business cycle. Figure 11 plots the responses of the model economy when we assume either that pessimism lasts on average 3.3 months, $\mathbf{p}^{\psi}_{\mathbf{pp}} = \mathbf{0.7}$, (red line with crosses) or for 20 months, $\mathbf{p}^{\psi}_{\mathbf{pp}} = \mathbf{0.95}$ (black line with squares). For the sake of comparison, blue continuous lines depict the responses of the baseline economy,

$\mathbf{p^{\psi}_{pp} = 0.85}$.

When the pessimistic state is very persistent, the economy converges on average towards the pessimistic sunspot limit for a much longer time. Therefore we now find that pessimism induces a more dramatic fall in output (2.5 percent relative to the intended steady-state) which occurs much later (7-8 months after the onset of pessimism). For the same reason, unemployment rises more and now reaches a peak of 7.4 percent with the same delay as output. On impact, the decline in vacancies is by construction the same as in the baseline experiment but the dynamics are, again, more persistent. Thus, we find that more persistence in the pessimistic beliefs amplifies the negative real effects of a sentiment shock. However, at the same time, we also find a larger decline in inflation and, consequently, in nominal interest rates which appears less consistent with the empirical evidence.

When pessimistic beliefs are more transitory, there is weaker evidence of partial adjustment of the real variables of the economy. Output falls for the first two months and then starts recovering yet remains depressed for 7-8 months after the wave of pessimism hits the economy. Unemployment follows a similar path to output with the largest increase happening within a month after the onset of pessimism while labor market tightness and vacancies both drop dramatically on impact and then recover relatively fast. Interestingly, and in line with our empirical analysis, we now find very little impact on inflation because agents perceive that beliefs may recover relatively quickly. This also means that consumption no longer displays a short run increase (due to savings on costs of changing prices) but instead declines for the first four months after pessimism. Hence, low duration of pessimism implies that the monetary impact of pessimistic beliefs are muted but also that the real effects are less persistent.

The size of the unemployment trap: In Figure 12 we further investigate how the results depend on the calibration of the level of unemployment in the low-activity steady state. Recall that we assume that this level of unemployment is nine percent in the baseline case (which is again depicted with the blue continuous line). We now show the results for a more dramatic case in which the unemployment rate is 10 percent in the unemployment trap (black line with squares), and for a less dramatic case where we set $\mathbf{u_{trap} = 7.5}$ percent (red line with crosses).

The key insight of this experiment is that, the worse is the *potential* outcome, the larger are the real effects of a sentiment shock. When $\mathbf{u_{trap} = 10}$ percent, output falls by almost 30 percent more than in the baseline and unemployment peaks at seven percent relative to 6.6 percent when assuming $\mathbf{u_{trap} = 9}$ percent. In contrast, when assuming $\mathbf{u_{trap} = 7.5}$ percent, the maximum decline in output and the increase in unemployment are both significantly muted.

Our analysis there suggests that economies that are more likely to experience high unemployment during crisis times are more susceptible to sentimental business cycles.

5 Conclusions

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

We model sentiment shocks as stochastic sunspots which cause shifts from optimism to pessimism in an incomplete markets general equilibrium model with heterogeneous agents with search and matching frictions in the labor market and nominal rigidities in the goods' markets, where multiple steady-state equilibria arise due to the presence of countercyclical earnings risk. Agent's pessimism about future labor demand leads to increases in precautionary savings and firms react by decreasing vacancy posting, which leads to increases in unemployment that become self-fulfilling and generate fluctuations that in many respects resemble the pattern we observed in the U.S. data. Common to the theory we have developed and the empirical results, the sentimental business cycles are dominated by a deterioration in the labor market.

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6 Tables and Figures

Table 1: **F-Statistics for Instrument Relevance Tests**

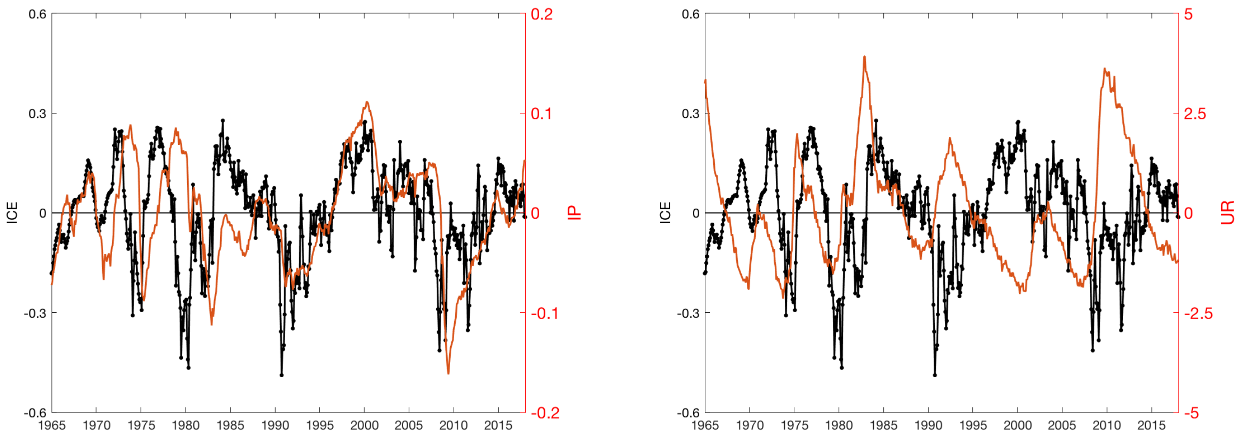
Part A: Benchmark VAR			
Sample	Proxy	F-test value (F^{HOM})	F-test value (F^{MOP})
1965:1–2007:8	MassFat_7	12.0	17.6
1965:1–2015:12	MassFat_7	11.2	5.2
1965:1–2018:11	MassFat_7	5.5	2.5
1965:1–2007:8	MassFat_3	9.6	8.2
1965:1–2007:8	$\text{MassFat}_7\text{Dummy}$	10.6	16.5
Part B: Alternative VAR specifications, 1965:1–2007:8			
Confidence	Observables	F-fest value (F^{HOM})	F-test value (F^{MOP})
ICC	Benchmark	2.9	2.7
ICS	Benchmark	10.0	13.3
BUS5	Benchmark	5.4	6.5
BUS12	Benchmark	8.9	18.6
ICE	CPI inflation	11.7	17.3
ICE	no SP500	9.7	18.9
ICE	no U12	9.1	13.1
ICE	no SP500, U12	7.5	13.5

Note: The table records the outcomes of F-tests for the null hypothesis that the instrument coefficient is zero in the first-stage regression for consumer confidence. HOM and MOP respectively denote the F-statistics for the null of standard conditional homoscedasticity and no serial correlation, and for the Montiel-Olea and Pflueger (2013) HAR-robust F-test.

Table 2: **Calibration**

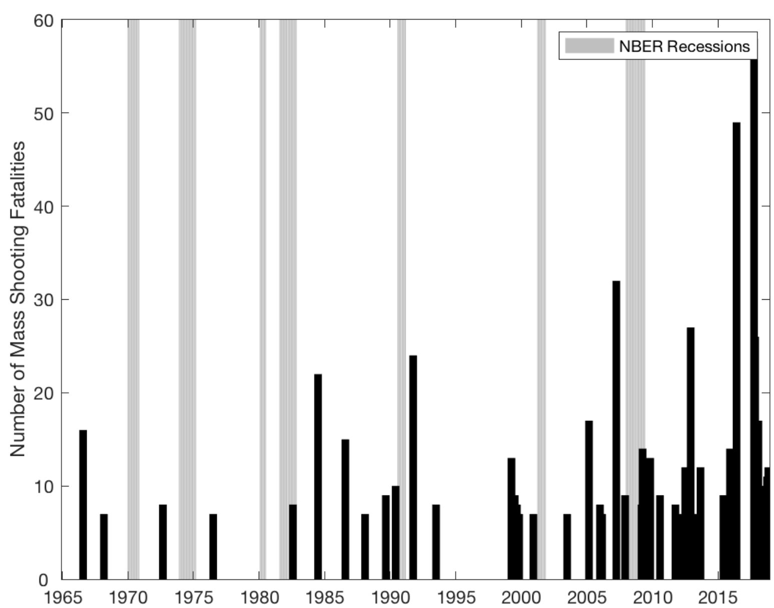
Parameter	Meaning	Value
$\overline{\mathbf{R}}/\overline{\Pi}$	steady state gross real interest rate rate	$1.035^{1/12}$
$\overline{\Pi}$	steady state gross inflation rate	$1.045^{1/12}$
μ	coefficient of relative risk aversion	2
$(c_e - c_u)/c_e$	steady state consumption drop upon job loss	15 percent
ζ	price contract length	10 months
γ	elasticity of substitution between varieties	8
$\mathbf{q_I}$	vacancy filling rate	0.23
$\mathbf{u_I}$	unemployment rate	5 percent
α	matching function elasticity	0.6
ω	monthly job separation rate	0.035
$(\kappa/\mathbf{q_I})/(3\mathbf{w_I})$	steady state hiring cost	4.4 percent
χ	wage flexibility parameter	0.001
A	productivity	1
ξ	share of entrepreneurs	1%
δ_π	coefficient of inflation in Taylor rule	1.5
$\mathbf{u_{trap}}$	unemployment trap rate	9 percent
p^{ψ}_{pp}	persistence of pessimism	0.85
Implied parameter values Intended steady state		
$\overline{m}$	match efficiency	0.32
$\eta_{\mathbf{I}}$	steady state job finding rate	39.9 percent
β	discount factor	0.989
$\Theta_{\mathbf{I}}$	wedge	1.0081
$\eta_{\mathbf{trap}}$	unemployment trap job finding rate	26.1 percent
$\mathbf{v_F}/\mathbf{v_I}$	free vacancies parameter	50.7 percent

Figure 1: Consumer Confidence vs. Industrial Production and Unemployment



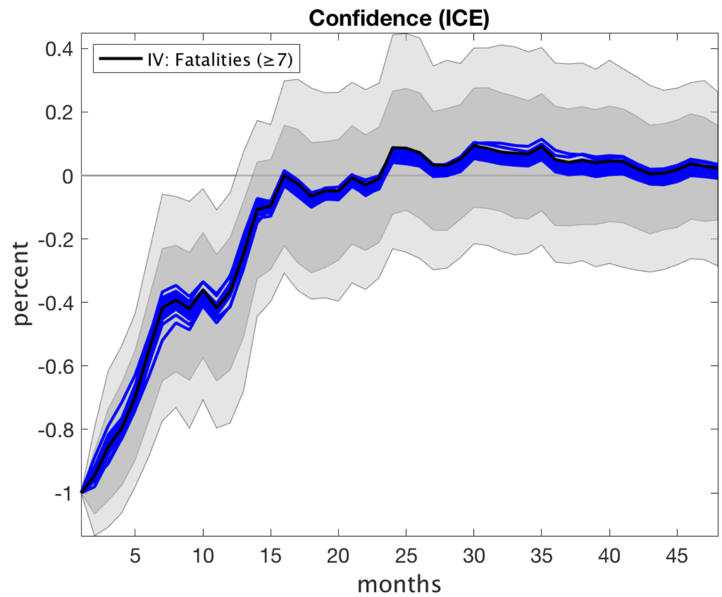
Note: The graph presents time series of detrended ICE against industrial production (left panel) and unemployment (right panel) from 1965:1 to 2018:11. All series have been detrended with fourth-order time polynomials.

Figure 2: Timeline of Mass Shootings and Fatalities



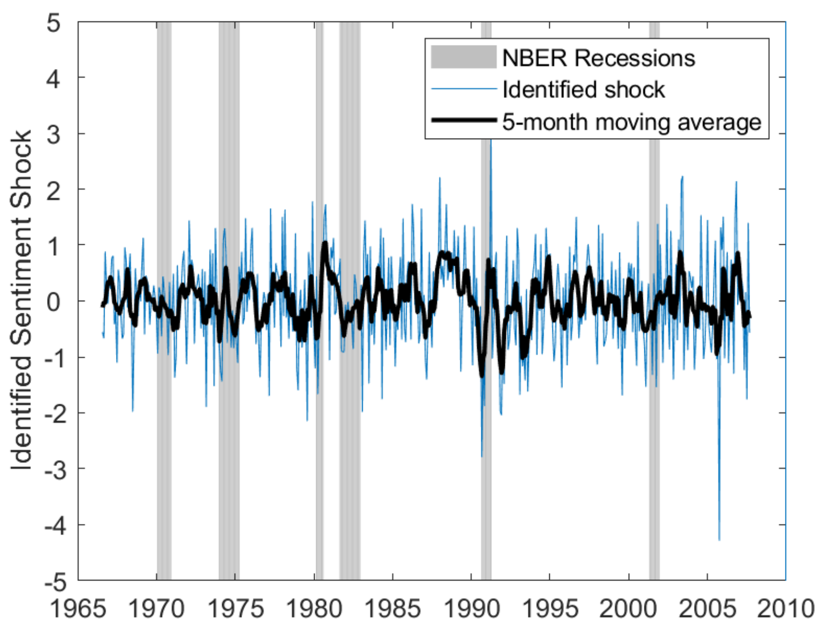
Note: The graph presents the timeline of fatalities in mass shootings with 7 or more victims over the period 1965:1-2018:11.

Figure 3: Confidence Response to the IV



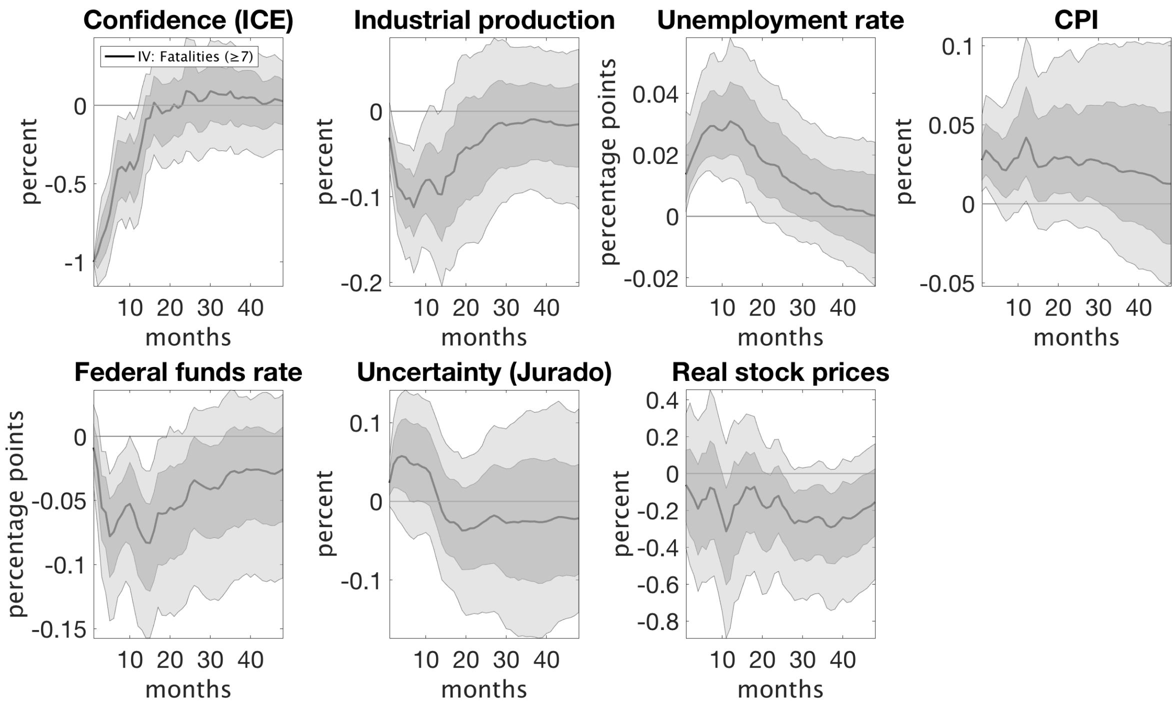
Note: The graph plots the responses of ICE to a sentiment shock. The continuous black line depicts the point estimate of the impact of the identified sentiment shock on the ICE in our benchmark specification. Dark grey and light grey areas represent 68 and 90 percent confidence bands based on the Montiel-Olea et al (2020) parametric bootstrap, respectively. Blue lines depict point estimates of the impulse response functions from specifications in which we exclude each of the 24 mass shootings with 7 or more fatalities, one at a time. The sample period is 1965:1-2007:8.

Figure 4: Historical Realizations of Sentiment Shocks



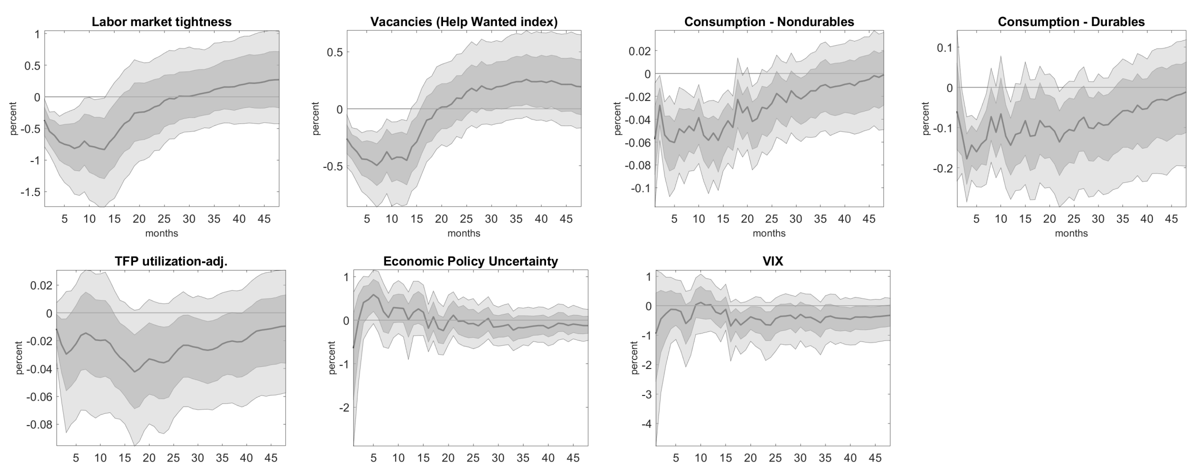
Note: The graph plots our identified shock series (blue line) and its 5-month moving average (black line) for our benchmark specification, where we use shootings with 7 or more fatalities as an instrument for consumer confidence. Grey shaded areas show NBER recessions.

Figure 5: Consumer Sentiment Shock IRF - Benchmark



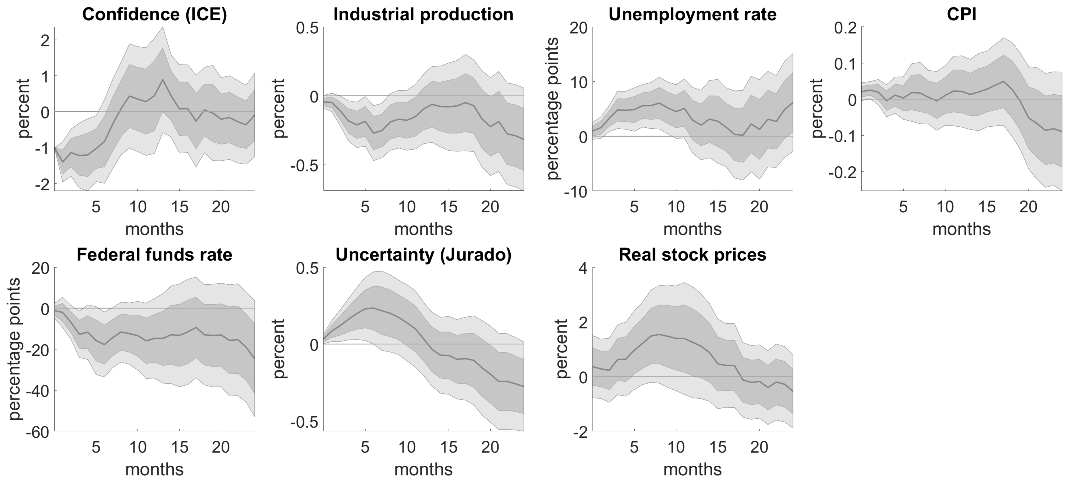
Note: The graph plots impulse response functions to a sentiment shock, for our benchmark specification. The continuous line depicts point estimates of the impact of the identified sentiment shock while dark grey and light grey areas represent 68 and 90 percent confidence bands based on the Montiel-Olea et al (2020) parametric bootstrap. The sample period is 1965:1-2007:8.

Figure 6: Consumer Sentiment Shock IRF - Additional Variables



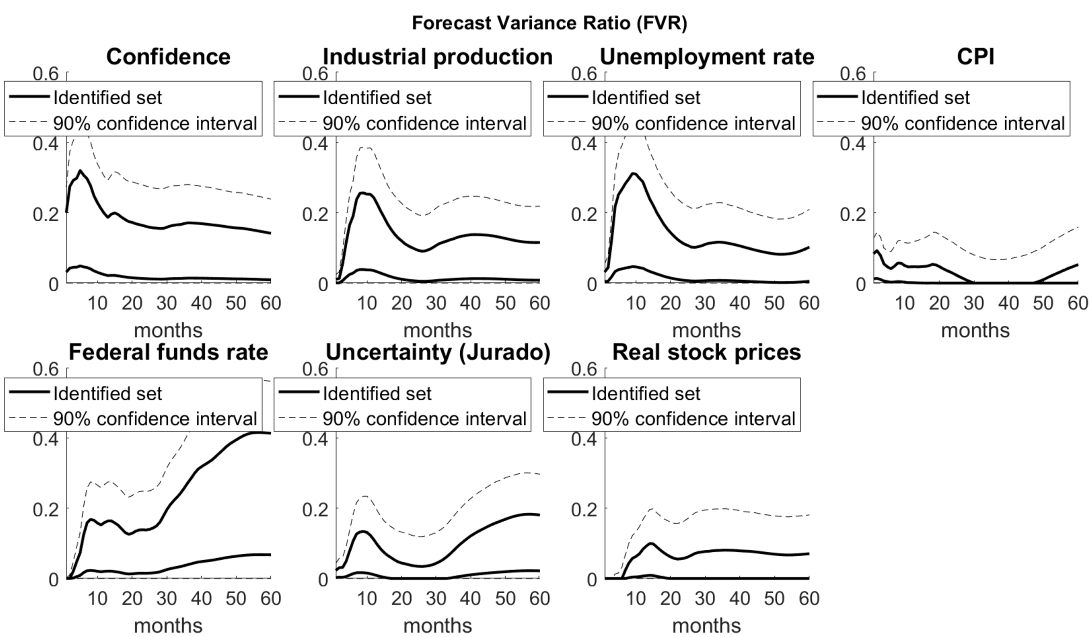
Note: The graph plots impulse response functions to a sentiment shock. The continuous line depicts point estimates of the impact of the identified sentiment shock while dark grey and light grey areas represent 68 and 90 percent confidence bands based on the Montiel-Olea et al (2020) parametric bootstrap. The sample period is 1965:1-2007:8.

Figure 7: Consumer Sentiment Shock IRF - using LP-IV



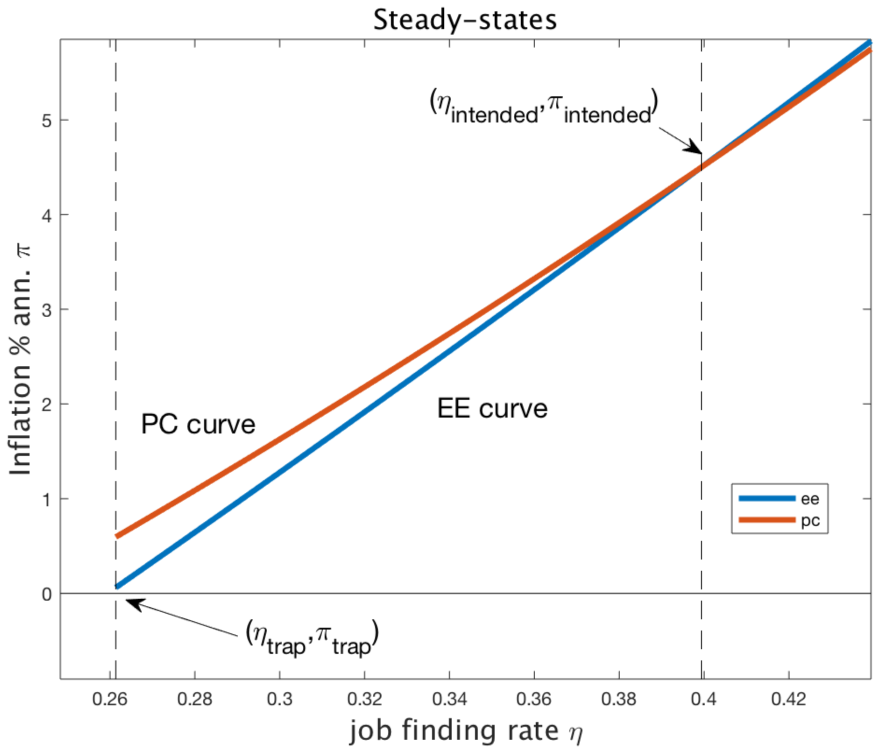
Note: The graph plots impulse response functions to a sentiment shock using the LP-IV methodology. The continuous line depicts point estimates of the impact of the identified sentiment shock while dark grey and light grey areas represent 68 and 90 percent confidence bands based on the Newey-West estimator. The sample period is 1965:1-2007:8.

Figure 8: Forecast Variance Ratios and 90% Confidence Bands



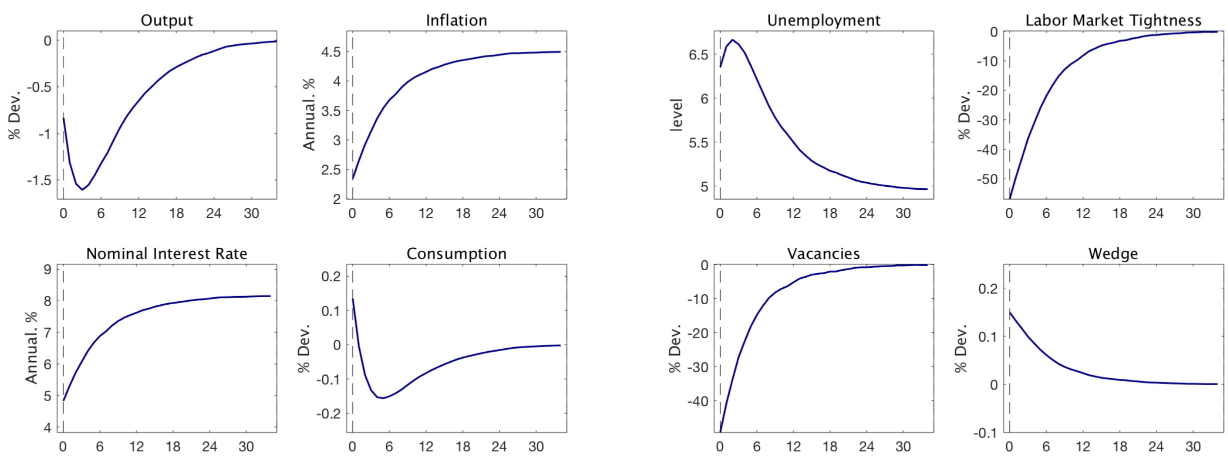
Note: The graph plots point estimates and 90 percent confidence intervals for the identified sets of forecast variance ratios. Bias-corrected estimates/bounds are set to lie in the [0, 1] interval. The sample period is 1965:1-2007:8.

Figure 9: A temporary unemployment trap driven by a sentiment shock



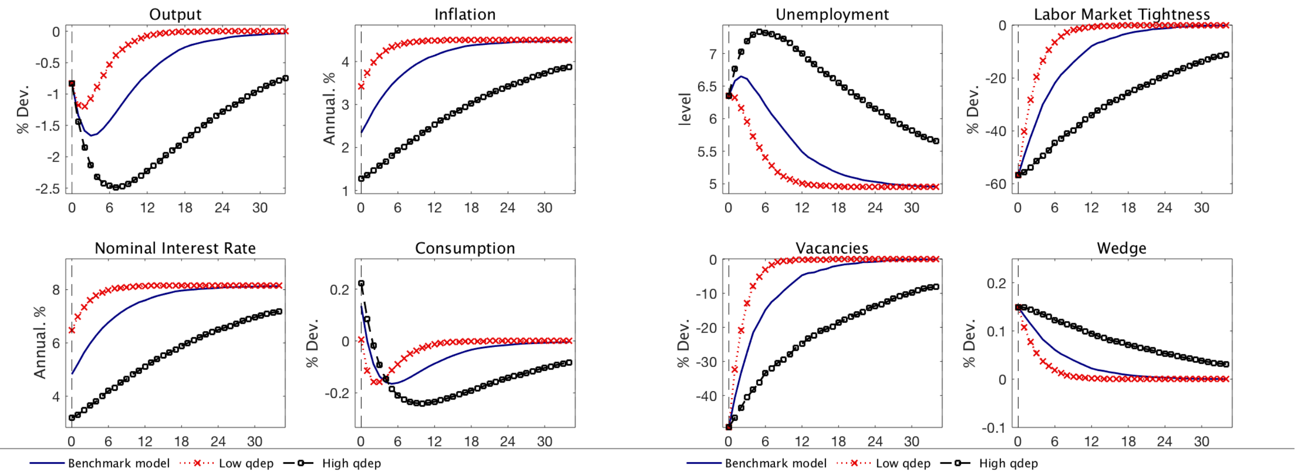
Note: The graph plots the steady-state relationships between inflation and the job finding rate. It is based on numerical evaluations using the parameter values discussed in the calibration exercise.

Figure 10: Dynamics in an unemployment trap driven by a sentiment shock



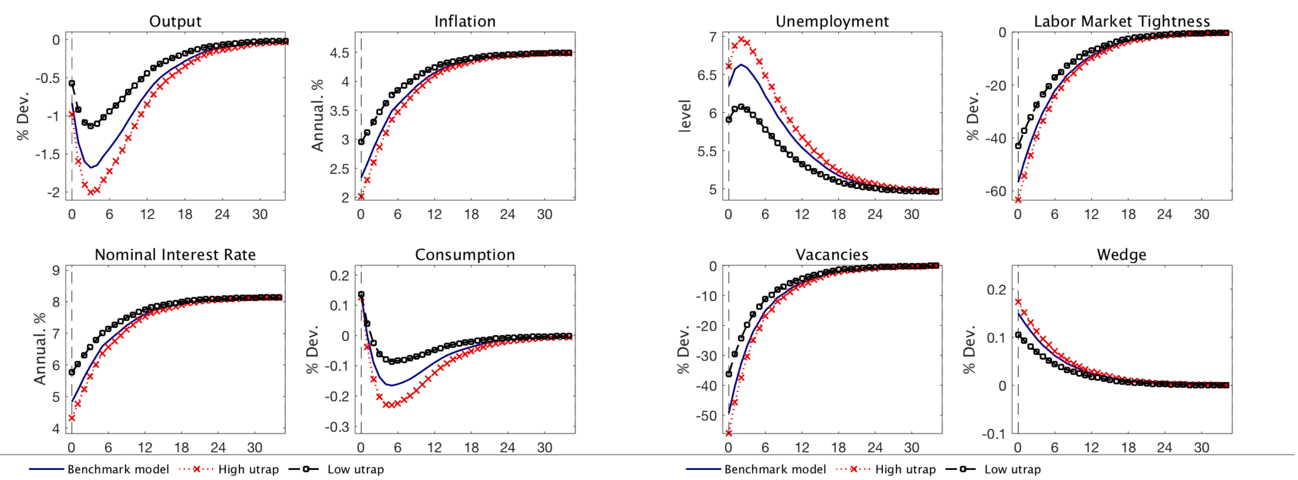
Note: The figure plots the dynamics of the key macro variables in an expectations driven unemployment trap. At time 0 pessimism prevails and the economy settles on a short run path towards pessimistic sunspot limit. It is based on numerical evaluations using the parameter values discussed in the calibration exercise.

Figure 11: Dynamics in an unemployment trap driven by a sentiment shock, persistence of pessimism



Note: The figure plots the dynamics of the key macro variables in an expectations driven unemployment trap. At time 0 pessimism prevails and the economy settles on a short run path towards the pessimistic sunspot limit. It is based on numerical evaluations using the parameter values discussed in the calibration exercise. Continuous lines present the responses of the benchmark economy, while squared black lines represent responses when the persistence of pessimism equals 0.99 and dotted crossed red lines when the persistence of pessimism equals 0.7.

Figure 12: Dynamics in an unemployment trap driven by a sentiment shock, size of the unemployment trap



Note: The figure plots the dynamics of the key macro variables in an expectations driven unemployment trap. At time 0 pessimism prevails and the economy settles on a short run path towards the pessimistic sunspot limit. It is based on numerical evaluations using the parameter values discussed in the calibration exercise. Continuous lines present the responses of the benchmark economy, while squared black lines represent responses when the unemployment trap equals 10 percent and dotted crossed red lines when the the unemployment trap equals 7.5 percent.