Sentimental Business Cycles*

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Abstract

We estimate the dynamic casual effects of consumer sentiments using fatalities in mass shootings in the U.S. as an instrument for autonomous changes in consumer confidence. 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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Keywords: Consumer confidence, demand shocks, incomplete markets, instrumental variables.

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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 to 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 common place circumstance. From 1965 to November 2018, there were no less than 581 fatalities in such shootings stemming from 42 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 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 in 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, stock prices and 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 show that 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. For sufficiently countercyclical income risk, 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 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 persistent 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), Makridis (2019), and Lagerborg (2017) 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 such events constitute a source of bad news which in itself should not derive from economic fundamentals.

To facilitate this, we produce a new monthly dataset of mass shootings in the U.S. for the sample period January 1965 to November 2018. The dataset is constructed by combining and augmenting information from three existing sources, MotherJones (2020), Duwe (2007), and The-Violence-Project (2019). MotherJones magazine, published by the Foundation for National Progress, maintains an open-source database documenting mass shootings in the United States. We use MotherJones (2020) as the primary source of data on mass shootings from August 1982. Grant Duwe, an American criminologist has collected a different dataset which was first published in his book entitled "Mass Murder in the United States: A History" (Duwe (2007)). Grant Duwe has supplied us with his updated dataset that covers a longer sample period going back to 1902 and ends in 2016. The Violence Project is a non-profit, non-partisan research center dedicated to reducing violence in society. The-Violence-Project (2019) has collected an alternative database on mass shootings which contains data for the 1960-2020 sample. These three datasets use similar but not quite identical definitions of mass shootings. We use a consistent definition of mass shootings and double check the data incident-by-incident for accuracy and consistency using publicly available news and court reports as well as information from Wikipedia. The mass shooting dataset that we construct is, to the best of our knowledge, the more consistent and complete time series on mass shooting available.

The MotherJones (2020) database documents public mass shootings in which the motive appeared to be indiscriminate killing, satisfying the following criteria: (i) minimum *four* fatalities excluding the perpetrator (who is also excluded from the victim count)[2], (ii) the killings were carried out by a lone shooter[3], (iii) the shootings occurred in a public place. The database includes also a handful of cases known as "spree killings" in which the killings occurred in more

[2]In the MotherJones database, they also include shootings with three fatalities from 2013 onwards. We use minimum four fatalities throughout the sample for consistency.

[3]We include along with MotherJones (2020) the Columbine massacre and the Westside middle school killings both of which have two perpetrators.

than one location in a short period of time, otherwise fitting the aforementioned criteria. Duwe (2007) defines mass shootings as "incidents that occur in the absence of other criminal activity (e.g., robberies, drug deals, gang 'turf wars,' et cetera) in which a gun was used to kill four or more victims at a public location within a 24-hour period". The Violence Project follows the Congressional Research Service definition, as "a multiple homicide incident in which four or more victims are murdered with firearms (not including the offender(s)) within one event, and at least some of the murders occurred in a public location or locations in close geographical proximity (e.g., a workplace, school, restaurant, or other public settings), and the murders are not attributable to any other underlying criminal activity or commonplace circumstance (armed robbery, criminal competition, insurance fraud, argument, or romantic triangle)." The definitions of the three databases are similar, yet the shootings reported differ as Duwe (2007) and The-Violence-Project (2019) include shootings excluded from the MotherJones' database as they are considered motivated by personal disputes.

We adopt the MotherJones definition of public mass shootings. We first cross-checked mass shootings reported in the three databases, making sure that they fulfill the criteria mentioned above. Next, we checked with newspapers and court reports on the circumstances of the shootings and the details such as the number of victims and fatalities. During this process we found several errors in the number of fatalities and victims reported by MotherJones that we have corrected. We augment the MotherJones dataset with data from Duwe (2007) and the The-Violence-Project (2019) databases excluding those episodes where the motive of the shooting was unambiguously a personal dispute. This procedure leaves a subset of events for which the circumstances of the shooting are ambiguous. In our baseline, we consider events that clearly fit the definition provided above. In the Online Appendix we examine the sensitivity of our results to including the ambiguous cases. Our dataset is available on our websites.

Our main instrument refers to larger public mass shootings with minimum seven fatalities excluding the perpetrator. The three databases agree on these events in the 1982:1 - 2018:11 sample with two exceptions. Both Duwe (2007) and the The-Violence-Project (2019) include two events that do not appear in the MotherJones (2020) database: a) a mass murder in Manley Hot Springs in 1984 where six villagers disappeared and b) The Copley Township shooting in August 2011 where Michael Hance tried to kill his girlfriend and her family and neighbors. Although the latter case started with killing family members, the killer subsequently shot neighbors indiscriminately and for that reason we include it in our baseline. For the former, although Michael Silka (the killer) had a shootout with state troopers the day after the killings, the motive of the killings is unclear and the crime is unresolved as some of the bodies of the victims were never found. We therefore follow MotherJones (2020) and exclude it.

In the 1965:1 - 1981:12 sample (where data from MotherJones (2020) are not available), Duwe (2007) and the The-Violence-Project (2019) agree apart from only the former database including the Bonners shooting in the South Side area of Los Angeles, California on April 22, 1973 (seven fatalities). This incidence started with an argument between the shooter and a friend of his mother but resulted in indiscriminate killings and we have included it in our baseline analysis, but the results are robust to excluding it.

From January 1965 to November 2018, there were 42 mass shooting events with seven or more fatalities with a total of 581 fatalities implying that these shootings on average resulted in approximately 14 fatalities. 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 with seven or more 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 with seven or more fatalities has increased over time from an average of one shooting approximately every 973 days prior to 1990, to one every 608 days between 1990 and 2000, and to one every 391 between 2000 and 2015, escalating to one shooting every 159 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 11.4 fatalities, a figure which has increased to 23.9 per shooting since 2015. 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.

In the Online Appendix we also discuss incidents with between four and six fatalities (which we use for robustness analysis). For these events, there are larger differences between the databases making this a more noisy instrument.

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 the consumption of non-durables and durables and labor market indicators, such as vacancy postings and labor market tightness. Finally, we investigate 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:

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

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

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

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

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

where $\Gamma\left(\mathbf{L}\right) = \mathbf{A}\left(\mathbf{L}\right)^{\mathbf{-1}}$ is square summable. We are interested in characterizing the causal impact of a single shock and therefore in obtaining a single column of $\mathbf{\Theta}_0$. 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 $S_t - proj\left(S_t|\mathbf{W}_t\right)$ 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:

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

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

The 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:

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

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

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

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

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 by the evidence of instrument strength.[4]

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.[5] 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.

[4] With strong instruments, inference can be carried out using a Delta method estimator of the covariance matrix, else other covariance estimators are available, see Mertens and Ravn (2019) for a discussion.

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

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 through 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 Sandy Hook shooting in Connecticut in 2012 (28 fatalities).[6] Lankford (2018) studies news coverage of the perpetrators of seven mass killings in the 2013–17 period and finds that mass shooters in many cases received more news attention than even celebrities such as sports stars.[7]

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 might also impact on psychological well-being. In a similar vein to mass shootings acting as an instrument for confidence at the national level, Lagerborg (2017) uses school shootings as an instrument for confidence at the local level, and shows that sentiment shocks have significant real effects. Abadie and Gardeazabal (2003) argue 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 public spending on policing and national security.

We first examine whether the instrument satisfies the relevance condition. Table 1 reports

[6] 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).

[7] 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) are 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.

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 11.0, while it is 14.7 when we correct for heteroscedasticity. Including data up to the end of 2015, the standard F-statistic increases to 15.8 while the HAR version falls to 6.8 which is, nonetheless, still well above the five percent critical value (3.8). When the sample is extended up to November 2018, the standard F-statistic remains above the five percent critical value at 7.3 while the HAR-robust F-statistic falls to 2.8. 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.

Our database also contains information on mass shootings with between four and six fatalities. Making use of this alternative instrument with four 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 media 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 11.7 and 17.1, 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 is less relevant when considering the ICC, i.e. consumers' perceptions of current circumstances. Focusing on the BUS12 and BUS5 indices, fatalities in mass shootings are particularly useful as a proxy for BUS12 and somewhat less 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 21 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 16 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 14 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).[8]

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

[8]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 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.

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 5 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 reaching its largest fall around seven months after the consumer sentiment shock[9]. Unemployment also displays a hump-shaped response, reaching its peak 13 to 16 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 and at the 90 percent level only for a couple of months.

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 both labor market tightness, the ratio of vacancy postings to unemployment, and vacancies fall for a long period and significantly so for around 14 months at the 90 percent level following

[9]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.

the worsening consumer sentiments. Those responses indicate 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 almost two years. The response of durable consumption is more severe yet somewhat 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, apart from couple of months around one year after the initial shock, see Figure 6). Hence, the identified sentiment shock is unlikely to be a news shock about TFP.

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 to derive forecast error variance decompositions bounds 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):

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

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 $(\gamma_h)_{h=0}^{H}$:

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

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.

We find 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 eight 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.

The LP-IV results indicate an insignificant response of consumer prices to the decline in consumer confidence. Similarly, the nominal interest rate falls but not significantly at the 90 percent confidence level. Likewise the response of stock prices is insignificant, 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):

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

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 VARs estimators[10].

Figure 8 presents point estimates and 90 percent confidence bands of the identified set for 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

[10]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.

shock contributes very little at very short horizons but the identified set indicates this shock explains 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, with FVR upper bound peaking at 23 percent and 27 percent, respectively, at a 6-month horizon. As far as consumption of durables is concerned, the FVR upper bound peaks at 18 percent and thereafter falls steadily with the forcast horizon, while for non-durables the FVR upper bound remains above 20 percent for forecast horizons beyond eight months.

By contrast, we find that the identified shock does not matter at all for real stock prices. For the CPI, the shock explains at maximum 10 percent of the FVR and much less than that at all other forecast horizons. We find a more significant impact of sentiments is the short-term nominal interest rate where the upper bound hovers around 15 percent for horizons beyond 5 months. The bounds of the FVR for uncertainty follow closely those that we estimate for industrial production.

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

Our empirical results show that autonomous changes in consumer confidence impact significantly on the economy, especially on labor market outcomes. We now provide a structural interpretation of the empirical findings.

In the literature (see, e.g Lorenzoni (2009), Blanchard *et al.* (2013), and Barsky and Sims (2012)), sentiment driven fluctuations are often interpreted in rational expectations models as the response of agents to noisy signals about current, or future fundamentals. Although our empirical strategy identifies the impact of autonomous changes in consumer confidence, the nature of the instrument that we adopt for identification does not sit easily with the noisy signal approach. In particular, it would seem questionable to interpret mass shootings as instrumenting for noise about current or future TFP[11]. Alternatively, we could model sentiments as fluctuations in deviations of higher-order beliefs from first-order beliefs that are decoupled from expectations about fundamentals such as TFP as in Angeletos *et al.* (2018). There are two issues with adopting this approach: a) the latter authors are focused on transient variations in sentiments while our results indicate longer lived impact and b) the nature of instrument we adopt for identification concerns large events for which expectations should be aligned.

We take a different and complementary approach and model sentiment driven fluctuations in an incomplete markets model with labor market matching frictions. In this framework, we model sentiment driven business cycles as temporary spurs of pessimism that generate transitions from a "good" (high activity/low unemployment) equilibrium towards a "bad" (low activity/high unemployment) equilibrium. We model such fluctuations by means of a stochastic sunspot which coordinates expectations and show that it generates sentimental business cycles dominated by labor market fluctuations as in the data. The sunspot theory that we propose follows a line of papers in macroeconomics which have considered various aspects of indeterminacy and sunspots, see Benhabib and Farmer (1994) for an authoritative survey. The model that we study adds to this literature that a combination of labor market frictions, incomplete markets, and price rigidities can pave the wave for stochastic sunspots.

There are two main reasons for why we go this way. First, in our setting, sentiment driven fluctuations are literally waves of pessimism beliefs without the need for confusion about fundamental variables. Secondly, our empirical results points towards the labor market outcomes as key drivers of such fluctuations. This is exactly the mechanism on our model. In particular, in our setting, pessimistic views about the future path of the economy spur precautionary savings which generate poor labor markets outcomes which make the pessimistic views self-fulfilling. For that reason, the model allows for persistent fluctuations in the economy, a feature that is hard to reconcile with noise driven models.

4.A The Model

We extend the analysis of Ravn and Sterk (2017, 2020) of a HANK model with labor market frictions. Relative to these earlier papers, we focus on this model's implications for temporary transitions towards a high unemployment/low activity outcome, transitions that we model using stochastic sunspots. We characterize the conditions under which such transitions can exist, their properties, and solve for the dynamic paths using a global non-linear solver. We stochastically simulate transitions towards the sunspot limit point and examine their properties in the light of

[11] A previous version of this paper, Lagerborg *et al.* (2018), considered modeling sentiment shocks as noisy signals about TFP unrelated to economic fundamentals.

the empirical evidence.

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:

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

$\mathbb{E}_s x_{s+h}$ 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.[12]

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

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:

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

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 all firms set the same prices and make the same vacancy posting and employment decisions. The equilibrium conditions are given by:

$$\begin{aligned}
\mathbf{w}_s^{-\mu} &= \beta \mathbb{E}_s \frac{\mathbf{R}_s}{\mathbf{\Pi}_{s+1}} \mathbf{w}_{s+1}^{-\mu} \left[1 + \omega \left(1 - \eta_{s+1}\right) \left(\left(\vartheta / \mathbf{w}_{s+1}\right)^{-\mu} - 1\right)\right], && (25) \\
1 - \gamma + \gamma \mathbf{mc}_s &= \phi \left(\mathbf{\Pi}_s - 1\right) \mathbf{\Pi}_s - \phi \beta \mathbb{E}_s \left(\frac{\mathbf{c}_{c,s+1}}{\mathbf{c}_{c,s}}\right)^{-\mu} \left(\mathbf{\Pi}_{s+1} - 1\right) \mathbf{\Pi}_{s+1} \frac{\mathbf{y}_{s+1}}{\mathbf{y}_s} && (26) \\
\mathbf{mc}_s &= \frac{1}{A} \left(\mathbf{w}_s + \frac{\kappa}{\mathbf{q}_s} - \lambda_{v,s} - (1 - \omega) \beta \mathbb{E}_s \left(\frac{\mathbf{c}_{c,s+1}}{\mathbf{c}_{c,s}}\right)^{-\mu} \left\{\frac{\kappa}{\mathbf{q}_{s+1}} - \lambda_{v,s+1}\right\}\right) && (27) \\
\mathbf{c}_{c,s} &= \frac{1}{\xi} \left(\mathbf{y}_s - \kappa \left(\mathbf{v}_s - v_{\mathbf{F}}\right) - \mathbf{w}_s \mathbf{n}_s - \frac{\phi}{2} \left(\mathbf{\Pi}_s - 1\right)^2 \mathbf{y}_s\right) + \vartheta && (28) \\
\mathbf{n}_s &= (1 - \omega)(1 - \eta_s) \mathbf{n}_{s-1} + \eta_s (1 - \xi) && (29)
\end{aligned}$$

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 drop 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:

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

When $\mathbf{v}_{j,s} > \mathbf{v}_{\mathbf{F}}$, 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 $\mathbf{v}_{j,s} = \mathbf{v}_{\mathbf{F}}$, 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. 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 the following two conditions:

$$1 = \beta\overline{R}\left(\frac{\Pi_{\mathbf{ss}}}{\overline{\Pi}}\right)^{\delta_\Pi}\frac{1}{\Pi_{\mathbf{ss}}}\left[1+\omega\left(1-\eta_{\mathbf{ss}}\right)\left(\left(\frac{\vartheta}{\overline{w}\left(\frac{\eta_{\mathbf{ss}}}{\overline{\eta}}\right)^{\chi}}\right)^{-\mu}-1\right)\right] \tag{38}$$

$$\left(1-\phi\beta\right)\left(\Pi_{\mathbf{ss}}-1\right)\Pi_{\mathbf{ss}} = 1-\gamma+\frac{\gamma}{A}\left(\overline{w}\left(\frac{\eta_{\mathbf{ss}}}{\overline{\eta}}\right)^{\chi}+\left(\kappa\bar{m}\left(\frac{\eta_{\mathbf{ss}}}{\overline{m}}\right)^{-\alpha/(1-\alpha)}-\lambda_{v,ss}\right)\left(1-\left(1-\omega\right)\beta\right)\right) \tag{39}$$

Let $\Pi^{PC}(\eta)$ denote the inflation rate consistent with (38) as a function of the job finding rate. This schedule is vertical at the job finding rate corresponding to $\mathbf{v_{ss}}= \mathbf{v_F}$ and otherwise upward sloping (as long as $\Pi > 1/2$). The positive slope of this schedule reflects that firms' marginal costs are increasing in η since more prosperous job market prospects for the unemployed induce both higher wages and higher vacancy filling costs.

Similarly, let $\Pi^{EE}(\eta)$ denote the inflation rate as a function of the job finding rates consistent with the employed workers' Euler equation (38). The slope of this schedule instead depends on structural parameters. Denote the incomplete markets wedge by $\Theta(\eta) = 1 + \omega(1-\eta)\left(\left(\frac{\vartheta}{w}\right)^{-\mu} - 1\right) > 1$ which enters (38). The response of this wedge to changes in the job finding rate determines the slope of the Euler equation.

In a frictionless labor market or with full insurance, Θ is independent of $\eta$and $\Pi^{EE}(\eta)$ is horizontal and independent of η. In this case, there is a unique steady-state where $\lambda_{\mathbf{v}} = 0$. We will refer to this as the *intended steady-state*. We impose that the intended steady-state (denoted by subscript $\mathbf{I}$ below) displays local determinacy and a necessary (but not sufficient) condition for this is that $\delta_\Pi > 1/\beta$. In the intended steady-state, inflation is on target, $\Pi_{\mathbf{I}} = \overline{\Pi}$, vacancies unconstrained, $\mathbf{v_I} > \mathbf{v_F}$ (consistent with $\lambda_{\mathbf{v},\mathbf{I}} = 0$), and the remaining variables follow as the solutions to the steady-state conditions above when imposing these two results.

However, the presence of incomplete markets impacts on the slope of $\Pi^{EE}(\eta)$. Were real wages very elastic, χ large, the incomplete markets wedge will tend to be procyclical. The reason is that in this case, the rise in real wages when the job finding rate rises give employed workers strong incentive to save in good times not only for intertemporal reasons but also for precautionary reasons. Therefore, $\partial\Theta/\partial\eta > 0$, which generates a negatively sloped $\Pi^{EE}(\eta)$ relationship which preserves the steady-state uniqueness of the economy.

Still, if income risk for employed workers is dominated by job loss risk, a case that we will refer to as countercyclical earnings risk, the incomplete markets wedge is stronger the worse the state of the labor market, $\partial\Theta/\partial\eta < 0$. In this case, the $\Pi^{EE}(\eta)$ schedule is positively sloped. Intuitively, worsening job finding prospects bring about precautionary savings which puts a downward pressure on the real interest rate and therefore on inflation (since $\delta_\Pi > 1$). When this countercyclical earnings risk is sufficiently strong, $\Pi^{EE}(\eta)$ may become steeper than $\Pi^{PC}(\eta)$.

In this case another steady-state arises where $\Pi^{EE}(\eta)$ intersects the vertical segment of $\Pi^{PC}(\eta)$. Ravn and Sterk (2020) refer to this as the "unemployment trap" (indicated by $\mathbf{u}$). This steady state features high unemployment and low inflation. In this stationary equilibrium,

$\lambda_{\mathbf{v},\mathbf{u}} > 0$ and $\mathbf{v_u} = \mathbf{v_F}$. The equilibrium allocation and inflation rate in this steady-state solves

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

A necessary and sufficient condition for the existence of the unemployment trap is that $\lim_{\mathbf{v}\to\mathbf{v_F}-}\Pi^{EE}\left(\eta\left(\mathbf{v}\right)\right) < \lim_{\mathbf{v}\to\mathbf{v_F}-}\Pi^{PC}\left(\eta\left(\mathbf{v}\right)\right)$. This condition may not be straightforward to check while the a necessary condition that $\partial\Pi^{EE}\left(\eta_{\mathbf{I}}\right)/\partial\eta_{\mathbf{I}} > \partial\Pi^{PP}\left(\eta_{\mathbf{I}}\right)/\partial\eta_{\mathbf{I}}$ is more likely to hold the more countercyclical is earnings risk. It follows from the definition of Θ that:

$$
\partial\Theta/\partial\eta = \omega\left[\mu\chi\frac{1-\eta}{\eta}\left(\frac{\vartheta}{w}\right)^{-\mu} - \left(\left(\frac{\vartheta}{w}\right)^{-\mu}-1\right)\right]
$$

Thus, strong countercyclical movements in earnings risk occurs when the utility drop in case of job loss (the last term inside the square bracket) dominates the impact of cyclicality of wages (the first term).

The unemployment trap steady-state can arise as a stationary equilibrium because of the combination of incomplete markets and demand-supply side complementarity due to sticky prices and monopolistic competition. When earnings risk is strongly countercyclical, lower job finding rates spur precautionary savings. Higher savings propensity, in turn, translates into lower goods demand. On the part of firms, lower goods demand gives less incentive to hire while lower job finding rates makes hiring cheaper. When the depressed demand effect dominates workers expectations of worsening labor market outcomes can become self-fulfilling taking the economy on a path towards the high-unemployment cum low output outcome eventually meaning that only those vacancies that can be filled for free are posted.

We stress that the allowance for "free vacancies" is not the source of the multiple steady-states but simply functions to avoid having a complete breakdown of the economy in the unemployment trap.

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 $p_{ij}^\psi = \Pr\left(\psi = \psi^i | \psi_{-1} = \psi^j\right) \in [0,1]$ for $j \in (o,p)$ where $\sum_i p_{ij}^\psi = 1$. 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:

$$\begin{aligned} \mathbf{n}_s &= g_z\left(\mathbf{n}_{s-1,}\psi_s\right),\ \mathbf{n}_{s-1,} \text{ given} && (40) \\ \mathbf{h}_s &= g_h\left(\mathbf{n}_{s,}\psi_s\right) && (41) \end{aligned}$$

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, 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}+(1-p_{oo}^{\psi})\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) &= (\gamma-1)+\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)(1-\omega)\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} &= (1-\omega)\,\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 $p^{\psi}_{oo} < 1$, the optimistic sunspot limit will be different from the intended steady-state due to the risk of agents losing confidence.

Calibration: Our calibration 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 2.5 percent. The assumed long run real interest rate equals its conventional value in the literature, while the inflation calibration corresponds to what was observed in the U.S. in the post Volcker period. We set the degree of risk aversion to $\mu = 2$, a standard value in the literature. Consumption is assumed to fall by 18 percent of the intended steady-state wage upon job loss and we calibrate accordingly $\vartheta = 0.82\mathbf{w_I}$. 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 12 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 3.3 percent per month. Next, we assume that the vacancy cost parameter, κ, is consistent with an average hiring cost of 3.6 percent of the quarterly wage bill. This is close to the estimates of Silva and Toledo (2009).

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 5.5 percent in the intended steady state. This implies that the monthly job finding rate, $\eta_{\mathbf{I}}$, is equal to 36.2 percent so that the average unemployment duration upon job loss is around 2.8 months. We calibrate the matching efficiency parameter, $\overline{\mathbf{m}}$, to target a monthly vacancy filling rate in the intended steady-state of 27 percent, which is consistent with the value assumed by e.g. Ravenna and Walsh (2008).

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

$$\beta = \frac{1}{R_I\left(1+\omega\left(1-\eta_I\right)\left(\left(\frac{\vartheta}{w_I}\right)^{-\mu}-1\right)\right)}$$

which implies at the annual frequency that $\beta^{12} = 0.86$. 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 seven 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 seven percent but also examine robustness to this assumption. Should this level of unemployment be attained, the job finding rate declines to 30.5 percent.

From the calibration of the unemployment trap, it follows that around 76 percent of vacancies are filled in the informal market when the economy is in the intended steady-state. The high level of this rate corresponds to many hires been filled by informal recruiting networks, hiring in spot markets, and switches of employees from temporal to permanent contracts, as reported by Galeotti and Merlino (2014) and Davis *et al.* (2013).

We assume that the intended steady-state is absorbing, $\mathbf{p}^{\psi}_{oo} = 1$, while the persistence of pessimism is calibrated to $\mathbf{p}^{\psi}_{pp} = 0.8$. This implies that when agents turn pessimistic, this state will last on average for 5 months which is consistent with the persistence of the drop in the consumer confidence index that we estimated earlier.[13]

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. As in Mertens and Ravn (2014), 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 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 $\mathbf{\Theta_I} = 1.01$ and $\partial\mathbf{\Theta_I}/\partial\eta_\mathbf{I} = -0.16$ 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

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

annualized inflation is 0.32 percent.

Dynamics in response to Sentiment Shocks: In Figure 10 we illustrate the dynamics of the economy during a sentimental business cycle. 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.

A wave of pessimism depresses economic activity. As pessimism sets in, output declines gradually reaching a maximum fall of approximately 0.6 percent relative to the intended steady-state after approximately three months. Parallel to the drop in output, consumption declines mimicking the dynamics of output.

As far as the labor market is concerned, pessimistic expectations bring about a increase in unemployment while vacancies and labor market tightness drop. 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[14]. The increase in the unemployment rate peaks at 0.6 percentage points two-three months after the onset of pessimism and 12 months later, unemployment has on average returned to its intended steady state value. Notice that, due to the partial downward adjustment of employment, unemployment will rarely 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 by 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 the Phillips curve is forward looking and agents at any point may turn optimistic. The inflation rate in the pessimistic sunspot limit is 1.7 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. According to the Taylor rule, the short term nominal interest rate, follows the inflation response.

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

[14]Since vacancies is a stock variable, we illustrate an MA(2) of the vacancies implied by the model.

persistent responses of unemployment. The model is obviously very simplified and, of course, we do not expect to match the empirical impulse responses very precisely. Nevertheless, the responses of output and unemployment implied by the model fit reasonably well the empirical estimates. Assuming a value of the decline in consumer confidence in the ball park of four percent, similar to the largest value of the identified shock in the data, output declines by about one percent at maximum while the unemployment rate rises 0.2 percentage points. The model instead implies a fall in output of 0.6 percent and an increase in unemployment of 0.6 percentage points for our calibration[15]. Below we examine the sensitivity of the theoretical responses to key parameters and show that we can get close to the empirical estimates for either output or unemployment.

Sensitivity Analysis

It is interesting to investigate how the results just discussed depend on key parameters in order to understand better the extent to which the properties of sentimental business cycles are robust. We focus attention on two parameters, the persistence of pessimism, $\mathbf{p}_{pp}^{\psi}$, and the level of unemployment in the unemployment trap.

Pessimism persistence: In the baseline calibration above we assumed that $\mathbf{p}_{pp}^{\psi} = 0.8$ implying an expected duration of pessimism of 5 months. We now look at two alternative calibrations, $\mathbf{p}_{pp}^{\psi} = 0.9$, which implies an expected duration of the pessimistic state twice that of the baseline, and $\mathbf{p}_{pp}^{\psi} = 0.6$, where the average duration is 2.5 months, half of the benchmark. We show the results in Figure 11 comparing the benchmark (indicated by the blue continuous line), with the high and low persistence cases (indicated with red lines with crosses and black lines with squares, respectively). In all cases, we simulate the model 2000 times and show the means of responses of the endogenous variables over these experiments.

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 (0.8 percent relative to the intended steady-state) which occurs later (5 months after the onset of pessimism). Interestingly, this estimate of the output decline is very close to what the empirical estimates indicate for one of the larger estimated shocks to consumer sentiments (as we argued above this is around one percent). Moreover, for more persistent pessimistic beliefs, consumption rises in the short run. This is due to the presence of Rotemberg costs of changing prices. When pessimism is more persistent, demand falls more which in itself drives down prices more than in the baseline calibration. In addition, due to the forward looking nature of price setting, as long as agents are pessimistic, the probability of reverting to optimism is smaller than in the baseline case which induces a sharper fall in prices.

[15]The drop in output is limited by the fact that labor is the only factor of production. In a previous version of this paper (see, Lagerborg *et al.* (2018), we have considered an extension of the model with capital and variable capital utilization that disconnected output from employment movements and allows for more elastic responses of output. However, solving this extended model with global methods is not feasible.

Both the impact on inflation and on consumption seem less consistent with the data than the dynamics in the baseline case.

Higher persistence of pessimistic beliefs also implies that unemployment rises more and now reaches a peak increase of 0.8 percentage points with the same delay as output. The decline in vacancies in the short run 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.

Results are symmetric when assuming low persistence of pessimism. This induces a smaller and earlier peak decline in output and in unemployment. We now find very little impact on inflation because firms perceive that the economy may recover relatively quickly and therefore are reluctant to cut prices. This also means that consumption falls on impact and starts recovering gradually towards the intended steady-state after two months. These responses resemble closely our empirical estimates. 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 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 seven 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 9 percent in the unemployment trap (black line with squares), and for a less dramatic case where we set $\mathbf{u}_u = 6$ percent (red line with crosses).

The key insight of these experiments is that, the worse is the potential outcome, the larger are the real effects of a sentiment shock. When $\mathbf{u}_u$= 9 percent, output falls by almost 50 percent more than in the baseline case and unemployment peaks at 6.5 percent relative to 6.1 percent when assuming $\mathbf{u}_u$= 7 percent. In contrast, when assuming $\mathbf{u}_u$= 6 percent, the maximum decline in output and the increase in unemployment are both significantly muted. Our analysis therefore 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. Using these events as instruments for changes in confidence, we show that exogenous drops in consumer confidence generate a persistent contraction in economic activity that affects substantially the labor market.

Lagerborg (2017) confirms that the patterns we reveal in aggregate US data hold true also in county level data when analyzing the effects of changes in confidence instrumented by school shootings. It would be interesting to extend our analysis to other countries for which similar type of dramatic events permits the use of the IV strategy. Such analysis could help establishing external validity of our results.

We model sentiment shocks as stochastic sunspots which cause shifts from optimism to pessimism in an incomplete markets general equilibrium model with heterogeneous agents. 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.

In this paper sentiments are modeled as sunspots that coordinate agents' beliefs in a HANK model with multiple steady states. As long as agents are pessimistic, unemployment rises and output falls as the economy converges towards an unemployment trap limit point. For that reason sentimental business cycles may be persistent even in a model with rational agents. This contrasts with theories that model sentiment shocks as noisy signals about fundamentals. In such settings, it is difficult to generate significant and persistent fluctuations in the economy in response to noise. The reason for this is that large volatility of the noise shocks will lead agents to ignore these signals while low volatility noise by construction cannot induce significant business cycles fluctuations. The model we have analyzed in this paper, however, can address this issue due to the amplification mechanism induced by the countercyclical income risk. It would be interesting in future research to combine these two alternative ways of thinking about sentiment shocks.

Ultimately, one would like to design policy to address sentiment driven business cycles. In our setting, the design of both fiscal and monetary policy have implications for whether the economy is prone to this source of macroeconomic instability. Monetary policy cannot impact on equilibrium allocations when the economy suffers a wave of pessimism but *can* affect the likelihood with which such events can occur. A more aggressive monetary policy stance helps alleviating the economy from such waves of pessimism through its impact on inflation expectations. Fiscal policy can also help in an ex-ante sense by stabilizing the precautionary savings motive through the provision of unemployment insurance. There are, however, also trade-offs that would be interesting to explore further. In particular, more generous unemployment insurance may make firms more reluctant to hire and more aggressive monetary policies may be problematic in circumstances where the divine coincidence fails. It would be interesting to explore these issues in detail in future work.

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6 Tables and Figures

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

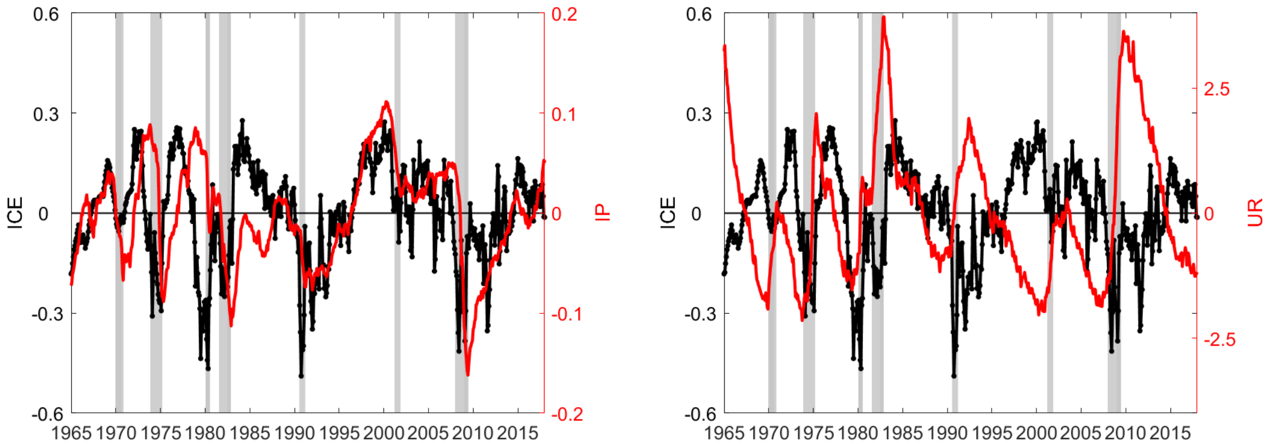
Part A: Benchmark VAR			
Sample	Proxy	F-test value (F^{HOM})	F-test value (F^{MOP})
1965:1–2007:8	MassFat_7	11.0	14.7
1965:1–2015:12	MassFat_7	15.8	6.8
1965:1–2018:11	MassFat_7	7.3	2.8
1965:1–2007:8	MassFat_4	7.4	7.0
1965:1–2007:8	$\text{MassFat}_7\text{Dummy}$	11.7	17.1
Part B: Alternative VAR specifications, 1965:1–2007:8			
Confidence	Observables	F-fest value (F^{HOM})	F-test value (F^{MOP})
ICC	Benchmark	4.6	4.5
ICS	Benchmark	10.4	10.3
BUS5	Benchmark	6.0	7.8
BUS12	Benchmark	8.5	16.4
ICE	CPI inflation	9.9	13.3
ICE	no SP500	8.8	12.9
ICE	no U12	8.6	10.8
ICE	no SP500, U12	6.8	9.8

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**

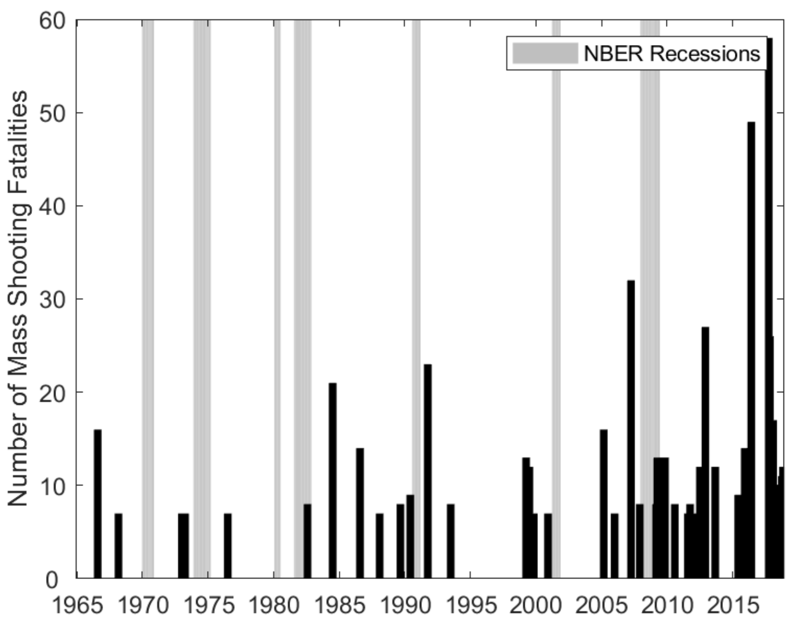
Parameter	Meaning	Value
$\overline{\mathbf{R}}/\overline{\Pi}$	steady state gross real interest rate rate	$1.035^{1/12}$
$\overline{\Pi}$	steady state gross inflation rate	$1.025^{1/12}$
μ	coefficient of relative risk aversion	2
$(c_e - c_u)/c_e$	steady state consumption drop upon job loss	18 percent
ζ	price contract length	12 months
γ	elasticity of substitution between varieties	8
$\mathbf{q_I}$	vacancy filling rate	0.26
$\mathbf{u_I}$	unemployment rate	5.5 percent
α	matching function elasticity	0.6
ω	monthly job separation rate	3.3 percent
$(\kappa/\mathbf{q_I})/(3\mathbf{w_I})$	steady state hiring cost	3.6 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
$\mathbf{u_u}$	unemployment trap rate	7 percent
p_{pp}^{ψ}	persistence of pessimism	0.8
Implied parameter values Intended steady state		
$\overline{m}$	match efficiency	0.32
$\eta_\mathbf{I}$	steady state job finding rate	36.2 percent
β	discount factor	0.987
$\Theta_\mathbf{I}$	wedge	1.01
$\eta_\mathbf{trap}$	unemployment trap job finding rate	30.5 percent
$\mathbf{v_F}/\mathbf{v_I}$	free vacancies parameter	76.1 percent

Figure 1: Consumer Confidence vs. Industrial Production and Unemployment



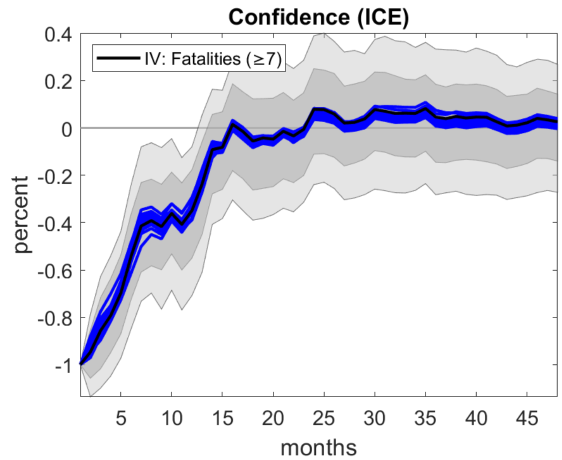
Note: The graph presents time series of detrended ICE against industrial production (left panel) and unemployment (right panel) from 1965:1 to 2018:11. All series have been detrended with fourth-order time polynomials.

Figure 2: Timeline of Mass Shootings and Fatalities



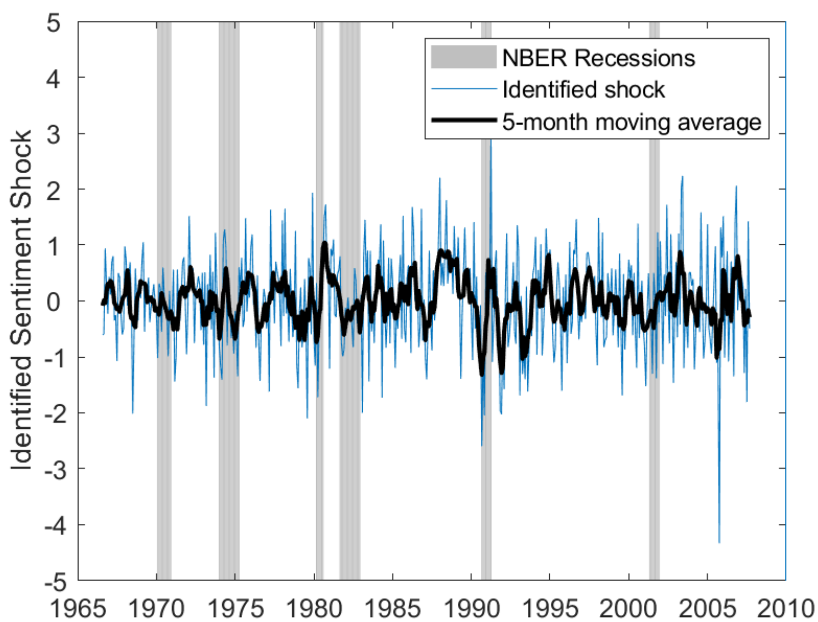
Note: The graph presents the timeline of fatalities in mass shootings with 7 or more victims over the period 1965:1-2018:11.

Figure 3: Confidence Response to the IV



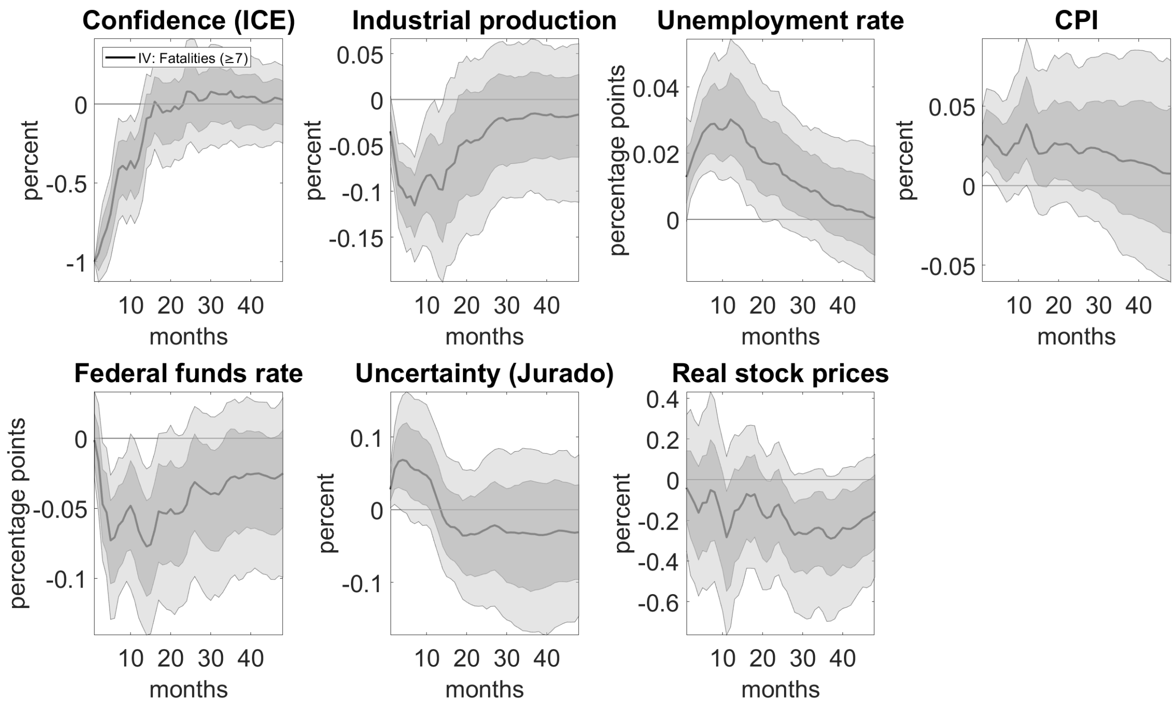
Note: The graph plots the responses of ICE to a sentiment shock. The continuous black line depicts the point estimate of the impact of the identified sentiment shock on the ICE in our benchmark specification. Dark grey and light grey areas represent 68 and 90 percent confidence bands based on the Montiel-Olea 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



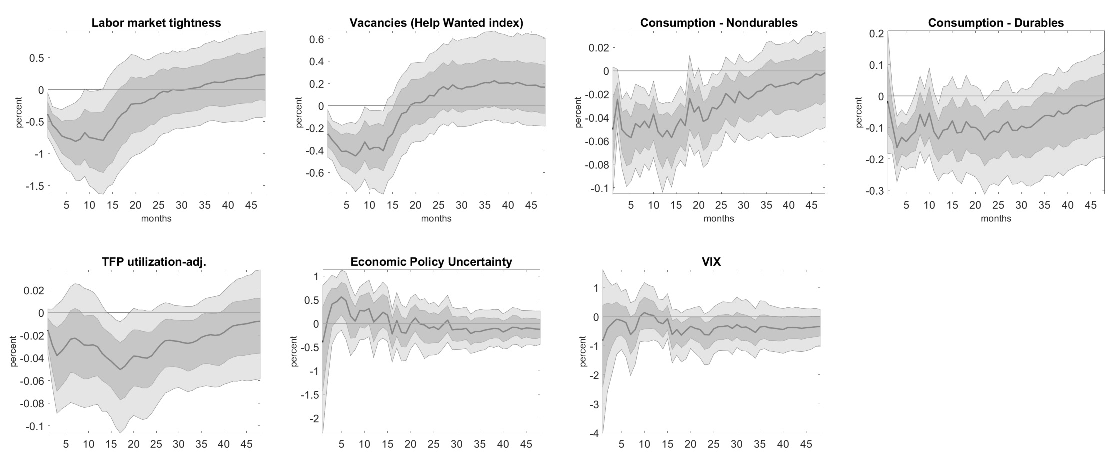
Note: The graph plots our identified shock series (blue line) and its 5-month moving average (black line) for our benchmark specification, where we use shootings with 7 or more fatalities as an instrument for consumer confidence. Grey shaded areas show NBER recessions.

Figure 5: Consumer Sentiment Shock IRF - Benchmark



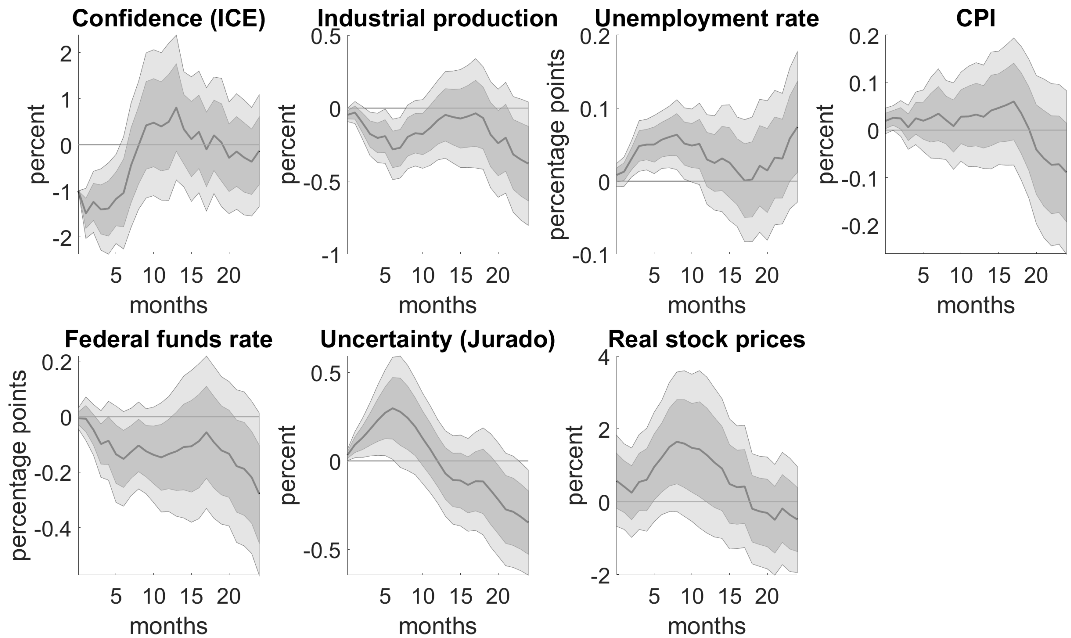
Note: The graph plots impulse response functions to a sentiment shock, for our benchmark specification. The continuous line depicts point estimates of the impact of the identified sentiment shock while dark grey and light grey areas represent 68 and 90 percent confidence bands based on the Montiel-Olea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

Figure 6: Consumer Sentiment Shock IRF - Additional Variables



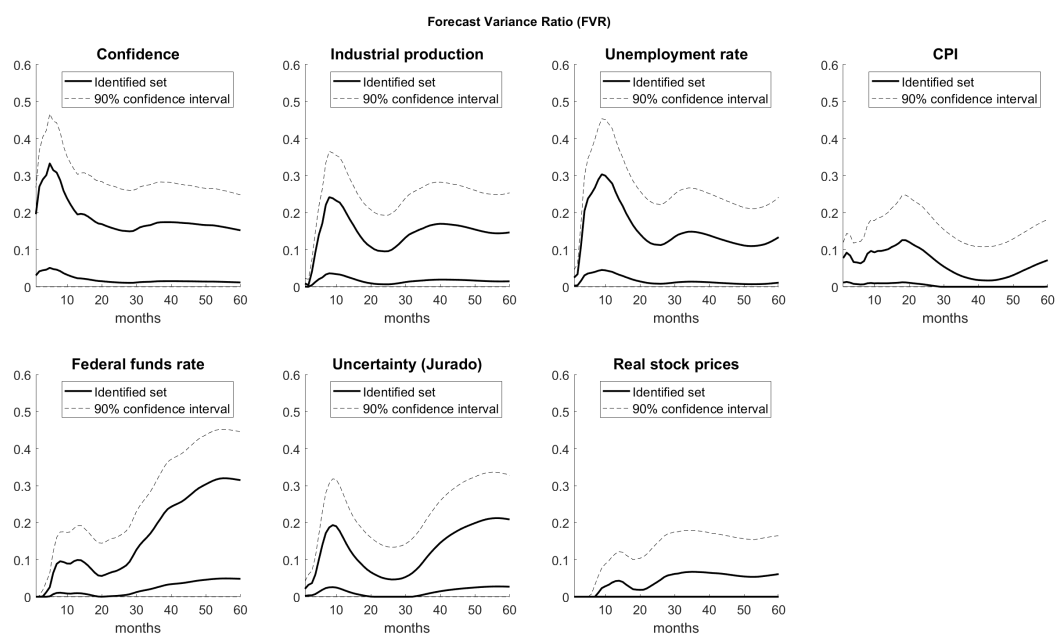
Note: The graph plots impulse response functions to a sentiment shock. The continuous line depicts point estimates of the impact of the identified sentiment shock while dark grey and light grey areas represent 68 and 90 percent confidence bands based on the Montiel-Olea et al (2020) parametric bootstrap.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

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



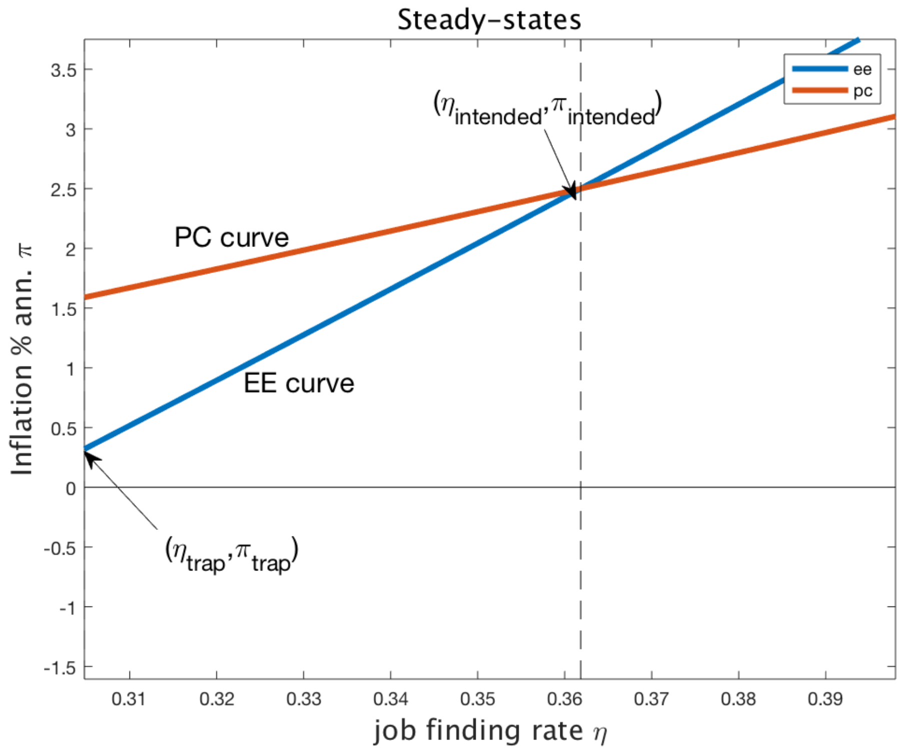
Note: The graph plots impulse response functions to a sentiment shock using the LP-IV methodology. The continuous line depicts point estimates of the impact of the identified sentiment shock while dark grey and light grey areas represent 68 and 90 percent confidence bands based on the Newey-West estimator.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

Figure 8: Forecast Variance Ratios and 90% Confidence Bands



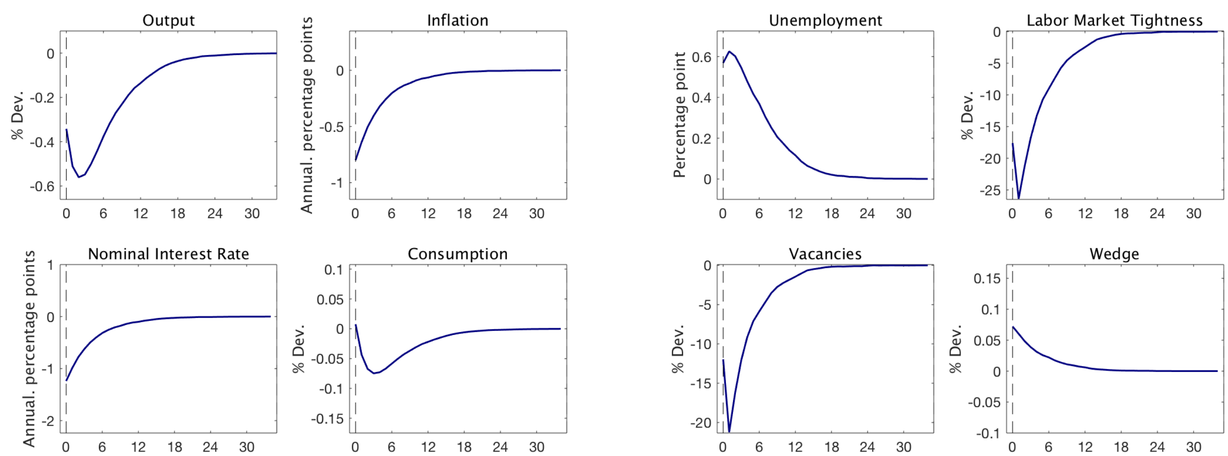
Note: The graph plots point estimates and 90 percent confidence intervals for the identified sets of forecast variance ratios. Bias-corrected estimates/bounds are set to lie in the [0, 1] interval. The sample period is 1965:1-2007:8.

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



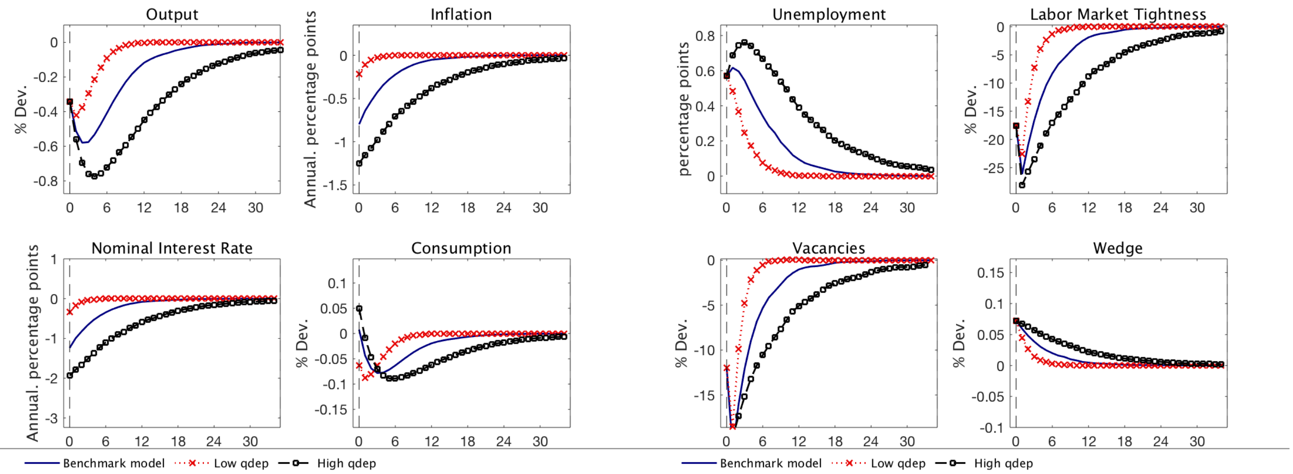
Note: The graph plots the steady-state relationships between inflation and the job finding rate. It is based on numerical evaluations using the parameter values discussed in the calibration exercise.

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



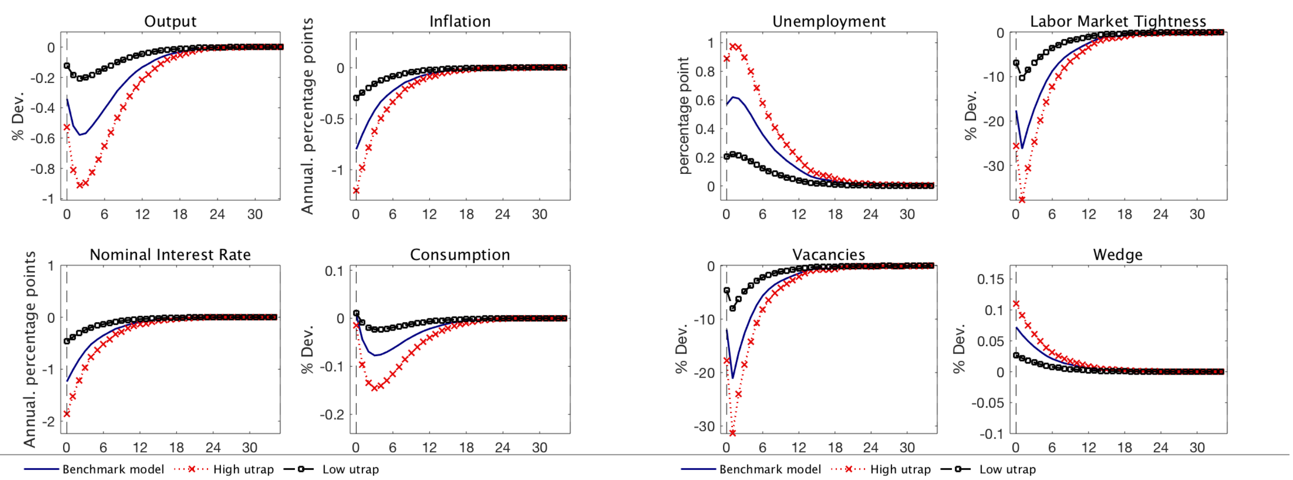
Note: The figure plots the dynamics of the key macro variables in an expectations driven unemployment trap. At time 0 pessimism prevails and the economy settles on a short run path towards pessimistic sunspot limit. It is based on numerical evaluations using the parameter values discussed in the calibration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