European University Institute

DEPARTMENT OF ECONOMICS

# Essays in Macroeconomics: Confidence, Business Cycles, and Fertility

Andresa Lagerborg

Thesis submitted for assessment with a view to obtaining the degree of Doctor of Economics of the European University Institute

Florence, 05 June 2018

European University Institute
**Department of Economics**

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I confirm that chapters 2 and 3 were jointly co-authored with Prof. Evi Pappa and Prof. Morten Ravn and I contributed 33% of the work. I moreover confirm that chapter 2 draws upon an earlier article we published in Nature Human Behaviour in May 2018.

I confirm that chapter 5 was jointly co-authored with Mr. Andrea Camilli and I contributed 50% of the work. The chapter was also published in the EUI Cadmus Working Paper Series in July 2017.

**Signature and Date:**

Andresa Lagerborg

May 18, 2018

# Abstract

This thesis comprises essays in macroeconomics across two main themes. The first studies the role of confidence shocks as a source of business cycle fluctuations using an instrumental variable approach. Exogenous drops in consumer confidence are identified by using school and mass shootings in the U.S. as natural experiments. Such autonomous drops in confidence are, in turn, found to sizably and persistently depress consumption and economic activity, raise prices, and reduce nominal interest rates. These empirical findings are shown to be consistent with a model in which negative confidence shocks reduce expectations of future technology, prompting consumers to save for wealth and precautionary motives, firms to reduce employment and investment while raising prices, and monetary authorities to reduce short-term nominal interest rates. These findings provide empirical evidence of a causal role of confidence in producing macroeconomic fluctuations.

The second theme studies household fertility decisions in relation to business cycles and underlying labor market institutions. Fertility in the U.S. is shown to be procyclical with respect to current economic conditions (negative unemployment shocks) and rise in response to consumer expectation and stock price news shocks - representing expected wealth effects anticipated by households. However, fertility is shown to be countercyclical with respect to highly transitory TFP shocks – such that couples choose to have children during recessions when the opportunity cost (forgone wages) is lower, i.e. the income effect outweighs the substitution effect. Moreover, labor market institutions not directly targeting fertility are found to affect average fertility rates through their impact on business cycles. Fertility rates are negatively associated with wage rigidities (which raise employment volatility) and positively associated with employment rigidities (which instead raise wage volatility).

*"Now, Voyager, sail thou forth, to seek and find."*

— *Walt Whitman*

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Finally, I would like to dedicate this thesis to my family. Mother and father, very proud parents, I am immensely grateful for your unfaltering support. My sister Elise, I love you to the moon and back. You mean the world to me.

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# Chapter 1

# Confidence and Local Activity: An IV Approach

## 1.1 Introduction

There is a long-standing debate in economics about the role of consumer sentiments in determining economic outcomes. One view is that consumer confidence merely reflects information about fundamentals, while an alternative stance, popular amongst policymakers, is that confidence also contains autonomous variations that may have causal effects on the economy.[1] The challenge in empirically testing the second view is how to isolate such exogenous variations in sentiments. This paper proposes an instrument that allows me to estimate the causal effects of sentiments on individual consumption appetite and its dynamic impact on local economic activity. I show that an autonomous drop in confidence makes individual households less positive about purchasing durables and induces a significant but short-lived increase in local area unemployment.

A pre-existing literature has examined the role of confidence in the U.S. economy by using aggregate confidence indicators drawn from the University of Michigan Survey of Consumers (e.g. Oh and Waldman 1990; Carroll et al. 1994;

[1]Policymakers and economists have repeatedly echoed the idea that drops in confidence lead to depressed spending and are a major cause of recessions, and that recoveries often hinge on restoring confidence in the economy. In the aftermath of the great depression, U.S. President Franklin Roosevelt in his inauguration speech proclaimed "the only thing we have to fear is fear itself", referring to the fact that fear about the economy was only making things worse. In a similar spirit, after the great recession, Akerlof and Shiller (2010) argued that "declining animal spirits are the principal reason for the recent severe economic crisis". Hall (1993) and Blanchard (1993) relate the long-lasting negative consumption shock associated with an exogenous shift in pessimism as the cause of the 1990-1991 recession.

Ludvigson 2004). I exploit subnational variation in confidence by looking at the individual level survey responses mapped to U.S. counties. I attempt to address reverse causality, whereby economic conditions affect confidence, by taking three main important steps. First, I consider a measure of confidence that regards the *aggregate* U.S. economic outlook, such that after controlling for time fixed effects, residual sentiments are orthogonal to national fundamentals. Second, I control for time-invariant individual economic circumstances by exploiting that a subset of respondents are surveyed twice. Finally, to control for endogeneity in local and individual sentiments, I employ an instrumental variable estimator. Specifically, I propose to instrument sentiments by county-level school shootings.

There are four main factors that make school shootings attractive as an instrument for sentiments. First, they do not entail large direct economic costs. For that reason, I argue they satisfy the so-called "exclusion restriction", whereby their impact on the economy occurs only indirectly through confidence. Second, I show that the timing and geographic dispersion of school shootings are orthogonal to local economic conditions and confidence, thereby satisfying "exogeneity". Moreover, there is substantial variation in school shooting incidents over time and across US counties, which enables the use of subnational data to employ panel regression methods. Finally, school shootings are shown to generate significant drops in individual and local area confidence in the county where they take place. Taken together, these factors imply that school shootings generate autonomous fluctuations in individual sentiments that are orthogonal to fundamentals.

That school shootings can affect individuals' emotions is supported by various findings in the literature. An event study of two related deadly attacks—the 2012 Sandy Hook School Shooting and the 2013 Boston Marathon Bombing—documents subsequent declines in subjective well-being and an increased feeling of meaningfulness across the U.S. and with larger effects in nearby states (Clark and Stancanelli, 2017). Another study argues that school shootings instigate widespread "moral panic" and "public fear" that is exacerbated by the media (Burns and Crawford, 1999). Moreover, many psychology studies have found that fear and negative moods, more generally, evoke pessimistic estimates and risk-averse choices by individuals.[2] As a result, it is plausible to consider

[2]Using an appraisal-tendency framework, Lerner and Keltner (2001) find that dispositional fear makes individuals pessimistic about a wider array of judgments and choices. A large literature also documents evidence that global positive and negative moods have residual effects on cognition and influence a wide range of judgments, e.g. regarding evaluations of personal efficacy, and satisfaction with consumer items, political figures, expectations about the future, and general life circumstances (Forgas and Bower 1987; Isen et al. 1978; Forgas and Moylan 1987; Kehner et al.

that the fear and negative emotions caused by school shootings can translate to general pessimism that is multi-dimensional, extending beyond concerns about public safety and security. In fact, this mechanism is one way of rationalizing my finding that local school shootings prompt pessimistic beliefs about national economic prospects.

Using a two-stage least squares approach, I analyze the impact of sentiments on economic outcomes. In the first stage, I show that school shootings constitute a strong instrument for local confidence, passing the weak instrument test (Stock and Yogo, 2005). Individuals residing in a county that is exposed to a school shooting, are found to significantly lower their confidence regarding the aggregate U.S. economic outlook relative to individuals in other counties. In the second stage, autonomous drops in confidence identified via this instrument, are found to significantly reduce individual attitudes towards purchasing consumer durables. This supports the idea that households adjust their spending plans in response to changes in sentiments. By contrast, effects of sentiments on larger ticket items such as cars or houses are found to be insignificant. The individual data, however, do not allow for a direct test of the impact of sentiments on *actual* consumption or other economic outcomes. To address this, I aggregate from individual to county level and study the impact of sentiments on local area unemployment, which can be thought to proxy local economic activity more generally. Specifically, I employ local projection (Jordà, 2005) IV methods to estimate the dynamic causal effects of sentiments on monthly county unemployment rates. I find that a decrease in sentiments significantly increases local unemployment for approximately one year. The impact is sizeable, a one standard deviation fall in confidence raises unemployment rates by up to 0.5 to 0.8 percentage points. Taken together, these findings indicate that sentiment shocks induce aggregate demand effects on the local economy that are short-lived.

My findings provide new empirical evidence on the role of sentiments in light of the existing literature. The first stage results, that there exist autonomous movements in sentiments, is in agreement with two closely-related studies that use an IV approach to identify exogenous variations in subnational confidence. The main innovation herein lies in the instrument used for identification. Moreover, key new results emerge from the second stage of my analysis. Mian et al. (2015) document no effect of sentiments on county-level consumer attitudes nor actual

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1993; Schwarz and Clore 1983; Mayer et al. 1992). Positive moods are shown to result in a more positive outlook whereas negative moods induce more pessimism.

consumption for durables and autos, and interpret this as evidence that sentiment shocks are neutral. By contrast, Benhabib and Spiegel (2016) document a real effect of sentiments on state GDP growth that is sizeable and long-lasting, up to three years. Finally, the significance of results in both papers is unchanged whether they use ordinary least squares (OLS) or IV and the instruments they use are highly related—political affiliation to the national government—reflecting the scarcity of natural experiments to study exogenous movements in consumer sentiment. Using a different instrument, I find that sentiment shocks have significant effects on consumer behavior—contrasting Mian et al. (2015)—and sizeably impact aggregate economic activity as measured by county unemployment rates, but with shorter-lived effects than suggested by Benhabib and Spiegel (2016) once endogeneity is taken into account.

My findings also reveal that it is important to account for endogeneity and measurement error in confidence. OLS regressions yield much smaller coefficient estimates of the impact of consumer confidence both on individual attitudes towards purchasing durables and on county unemployment rates, reflecting likely attenuation bias due to measurement error in confidence.[3] Moreover, OLS estimates suggest that the sentiments also affect individual consumer buying attitudes for larger items (cars and houses) while the impact on county unemployment rates are more persistent (lasting up to three years), reflecting the likely presence of endogeneity in confidence.

Additionally, I show that results are robust to a variety of sensitivity tests that consider alternative school shooting instruments, changes in the baseline specification, and different measures of confidence. I also present evidence of heterogeneous effects relating to individual and county characteristics. I find that shootings affect sentiments: (i) more for females and higher income and education individuals, and (ii) less in counties with conservative political preferences, stronger gun culture, rurality and remoteness, higher net migration rates, and higher share of creative employment. For these latter effects I do not claim causality; they are pure correlations and I remain agnostic as to their rationale.

The results of this paper have relevant implications for economic theory and practice. From a theoretical perspective, they provide empirical support for models of belief or expectation-driven business cycles. For forecasters, measures of confidence are shown to carry information unrelated to economic fundamentals

[3] In the presence of endogeneity but no measurement error, OLS estimates would constitute an upper bound for IV estimates.

that is still relevant for predicting economic fluctuations. For policymakers, it is important to consider that the way in which announced policies translate into public confidence will ultimately affect how they impact the economy. Moreover, understanding how sentiment shocks propagate is key to designing appropriate policy responses. Finally, a potentially crucial role also emerges for the media in transmitting fear and influencing public confidence.[4]

The remainder of the paper is structured as follows. Section 1.2 provides a review of the related literature. Section 1.3 describes the data and discusses evidence as regards endogeneity of sentiments and exogeneity of school shootings. Section 1.4 presents the methodolology and results of my analysis of how sentiment shocks impact individual consumer buying attitudes and county unemployment rate dynamics. In addition, robustness checks are described in Section 1.5 and evidence of heterogeneous effects is presented in Section 1.6. Finally, Section 1.7 concludes.

## 1.2 Related Literature

There are, broadly speaking, two main views on the role of confidence shocks in generating macroeconomic fluctuations. The first view is that of *news*, posing that confidence measures contain information about current and future economic fundamentals, in the spirit of Pigou (1926) and more recently revived by Beaudry and Portier (2006). The second is that of *animal spirits*, in the words of Keynes (1936), positing that autonomous fluctuations in beliefs, orthogonal to economic fundamentals, can have causal effects on economic activity. This is the interpretation given to sentiment shocks that is the focus of this paper.

One approach taken in the literature to separate these two effects is to control for as many fundamentals as possible, attributing residual changes in confidence to animal spirits. A few empirical papers show that changes in confidence unexplained by economic fundamentals are associated with spending shocks but effects are found to be temporary and small (Oh and Waldman 1990; Carroll et al. 1994; Starr 2012; Ludvigson 2004).

[4]This is consistent with findings that county exposure to pessimistic national news significantly contributed to depressing employment during the Great Recession (He, 2017).

To assess the quantitative role of animal spirit shocks in driving business cycles several other papers have estimated DSGE models and structural VARs augmented with sentiments. Sentiment shocks identified in SVARs are assumed to be orthogonal to fundamentals and have only transitory impact on economic activity.[5] Under this identification assumption, Barsky and Sims (2012) and Fève and Guay (2016) conclude that most of the variations in consumer confidence measures derive from survey respondents reacting to news about current and future fundamentals. In contrast, predictions from models by Lorenzoni (2009) and Angeletos et al. (2015) suggest the potential for sizeable amounts of noise-driven volatility in the short-run.[6]

This paper is closely related to a small literature that uses instrumental variables to identify exogenous movements in confidence. Using a closely related instrument, Lagerborg, Pappa, and Ravn (2018) consider mass shooting events in the U.S. as an instrument for residual confidence in a Proxy VAR model (Mertens and Ravn, 2013) estimated using aggregate U.S. data. Negative confidence shocks, instrumented by mass shooting events, resemble aggregate demand shocks in the short run that trigger downturns during which unemployment rises, output and durable goods consumption fall, and household personal savings rates rise, consistent with a shift from consumption to savings.

More closely related to the current paper, Mian, Sufi, and Khoshkhou (2015) and Benhabib and Spiegel (2016) both exploit subnational variation in consumer confidence combined with IV techiniques to evaluate the impact of exogenous variations in sentiment. Mian et al. (2015) consider a specific type of sentiment shock, relating to confidence about government economic policy, and instrument county-level sentiment using cross-sectional variation in constituent ideology interacted with the timing of two U.S. presidential elections that led to the loss of the incumbent president. They find that counties more ideologically predisposed toward the losing party experience a relative decrease in optimism, yet this does not

[5]Note that this assumption is inconsistent with predictions of models with multiple equilibria.

[6]Lorenzoni (2009) compares the size of demand disturbances generated by noise shocks in a calibrated model under different parameterizations and compares them with demand disturbances in VARs, suggesting that noise shocks can produce a sizeable fraction of observed demand-side volatility. Angeletos et al. (2015) estimate a DSGE model augmented with a sentiment-type confidence shock and find that this shock accounts for the bulk of business cycle fluctuations and closely mirrors the main factor accounting for business cycle fluctuations estimated using a dynamic factor model.

translate to lower consumer spending nor buying attitudes for durables and autos. They interpret their null result as suggesting that sentiments regarding government economic policy have no real effects. By contrast, Benhabib and Spiegel (2016) estimate a strong relationship between state-level expectations concerning future national output growth and state output growth lasting up to three years. This result is preserved when they instrument state-level confidence using the share of congressmen from the political party of the sitting president. They interpret this result as suggesting that sentiment influences aggregate demand. Their finding that sentiments have strong and persistent real effects contrasts Mian et al. (2015) even though both papers use very closely related instruments for sentiments: political affiliation to the national government.

I contribute to the existing literature on the following fronts. First, I propose an instrument with several advantages, that has not been explored before. Second, I consider improved measures of local sentiment at the individual and county levels where I reduce noise by limiting the analysis to individuals that respond twice to the consumer confidence survey. Finally, my results have implications for the debate on the real effects of sentiment shocks. I find evidence that these shocks have significant impact on consumer behavior—contrasting Mian et al. (2015)—and sizeably impact aggregate economic activity as measured by county unemployment rates, but with shorter-lived effects than suggested by Benhabib and Spiegel (2016). More generally, my results suggest that animal spirit shocks can induce demand effects as suggested in the early macroeconomic literature (e.g. Keynes 1936).

Other branches of the literature have proposed related shocks as drivers of business cycles. A parallel emerges to the literature that uses natural experiments such as natural disasters, terrorist attacks, and political events as instruments for uncertainty shocks (Baker and Bloom, 2013). Yet, the literature unanimously regards uncertainty shocks as time-variations in second order moments (volatilities) associated with business conditions, thereby affecting fundamentals of the economy (e.g. Bloom 2009; Bloom et al. 2012). Sentiments also relate to papers that study the role of news versus noise in explaining economic fluctuations (e.g. Beaudry and Portier, 2006). News shocks are tied to signals about future technology and the long-run macroeconomic outlook, precisely capturing information about future fundamentals. By contrast, sentiment shocks distinguish from uncertainty shocks and news shocks in that they do not reflect changes in fundamentals of the economy.

Finally, sentiment shocks relate to a voluminous theoretical literature involving self-fulfilling changes in consumer sentiments or sunspots. In a multiple equilibira setting, sentiments can constitute a driving force that randomizes across these equilibria, consistently with rational expectations (e.g. Diamond 1982; Benhabib and Farmer 1999). Even in a setting in which the fundamental equilibrium is unique, informational frictions and incomplete markets could bring about sentiment-driven stochastic equilibria. (e.g. Cass and Shell 1983; Angeletos and La'O 2013).

## 1.3 Data description

### 1.3.1 Individual Sentiments and Consumption Appetite

**Sources and Measurement**

Individual-level data on confidence were obtained from the Thomson Reuters University of Michigan Survey of Consumers, a nationally representative survey with approximately 500 randomly selected individuals interviewed across the U.S. each month. Given the small number of interviews for each county-month, a simple measure of average local confidence would inherit substantial noise from individual biases. Instead, I make use of the fact that two thirds of interviewees have a follow-up interview six months later, a feature of this survey which has not yet been explored in the related literature (e.g. Mian et al. 2015; Benhabib and Spiegel 2016), and compute the six-month change in confidence for the same individual. This enables me to reduce noise stemming from respondent fixed effects, constituting a considerable improvement in the measure of variations in local sentiment. During the sample considered, which spans from January 2000 to June 2017, a total of 105,533 interviews were conducted, of which 40,239 respondents were interviewed twice. Mapping individuals to their counties of residence and excluding those who have migrated counties, leaves 40,009 observations in the sample.[7]

Sentiment is defined as consumer confidence about national economic conditions. More precisely, it quantifies how individuals respond to the following

[7] I also check the quality of matched responses. For 98% of respondents match quality is high, measured by stable gender and age changes of at most 1 year. Results are robust to dropping poor matches from the sample.

survey question: "*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 5 years or so, or that we will have periods of widespread unemployment or depression, or what?*" Responses take discrete values between 1 and 5, which I re-order as increasing in confidence (see Figure A.1).[8] An analogous question is also asked regarding national economic conditions during the next 12 months, yet this measure has a higher correlation with current economic conditions, making it more susceptible to inverse causality concerns. Moreover, another advantage of using this survey question is for comparability, since this same measure of confidence concerning national output growth over a 5 year horizon is also used by Benhabib and Spiegel (2016). The maintained assumption is that counties are sufficiently small that attitudes about the local economy will not distort the response about national economic conditions. Assuming that fundamentals of the national economy are common to all individuals, and can be captured by time fixed effects, the residual component can be attributed to sentiments. As such, an individual that is more or less confident about national output growth than the average, is considered to be optimistic or pessimistic, respectively.

To analyze the impact of sentiment on consumer behavior, I consider self-reported spending plans that reflect sentiment over whether it is a good time to purchase consumer durable goods defined as "major household items" (DUR), cars (CAR), and houses (HOM). To control for changes in personal financial conditions (PAGO), I use responses to the question: "*are you better off or worse off financially than a year ago?*"[9] Figure A.2 plots histograms for these different indicators, where responses take discrete values 1, 3, and 5 that I again re-order as increasing in more positive consumer buying attitudes and improvements in personal finances. Finally, to study heterogeneous effects, I also relate variations in sentiments to individual characteristics reported in the survey such as gender, age, education, income quintile, number of children in the household, and marital status.

#### Descriptive Statistics and Endogeneity

[8]Note that the convention that indicators are increasing in confidence is adopted throughout the analysis.

[9]These two questions on current financial well-being and buying attitude for durables, make up the commonly-used aggregate index of current economic conditions (ICC). Similarly, the index of consumer expectations (ICE) is constructed based on three questions: expectations about national economic conditions 1 and 5 years ahead, as well as expected improvements in personal finances 1 year ahead. The Michigan Survey's well-known overall index of consumer sentiment (ICS) is then computed as the relative favorability score of these five broad sub-questions, combining ICC and ICE.

Table A.1 (column 1) shows how confidence regarding the national economic outlook relates to various individual characteristics.[10] Controlling for time fixed effects, which account for nation-wide economic conditions, higher confidence can be attributed to optimistic sentiments that are orthogonal to national fundamentals. Females are shown to be, on average, less confident than males. Individuals are more confident in their youth and old age, but less so in their mid-years. Individuals with higher education and income are also more confident, possibly reflecting better employment and financial prospects. Improvements in personal finances also make individuals more confident. Moreover, residing in counties with higher unemployment depresses individual confidence. These last three facts provide suggestive evidence that concerns over endogeneity are well-founded: individual and local economic conditions are found to affect sentiments.[11]

Individual characteristics and economic conditions affect consumer buying attitudes for durable goods, cars, and houses with a similar pattern (columns 2-4). One notable and interesting distinction is that the relationship to age reverts, i.e. individuals in their mid-age have more optimistic attitudes, when it comes to buying houses. This is consistent with empirical evidence that homeownership rates over the life cycle rise steeply for this age group and supports the idea that buying attitudes reflect an "intention to purchase".

### 1.3.2 County Unemployment

Data on county unemployment rates is obtained at monthly frequency from the Local Area Unemployment Statistics of the Bureau of Labor Statistics (www.bls.gov/lau). Since the data is only available on a non-seasonally adjusted basis, I used the Census Bureau's X13 procedure to seasonally adjust unemployment. Figure A.3 plots confidence against unemployment rates for the U.S. during the sample considered. There are two major upswings in unemployment rates, starting in 2001 after the dot-com bubble collapsed and in 2008 during the Great Recession. While county-level unemployment rates track national rates (with a

[10]Marital status, the number of children in the household, and region of residence are insignificant and therefore not reported.

[11]In the same way that economic conditions are shown to affect sentiments in levels, this relationship may be present in differences. I find that changes in improved personal finances increase optimism whereas changes in county unemployment rates have no significant effect (see e.g. Table A.7).

correlation coefficient of 0.55) there is substantial cross-sectional variability, with county average unemployment rates ranging from 2.2 to 21.3 percent. Correlation coefficients and summary statistics for consumer confidence survey variables and unemployment rates are presented in Table A.2.

### 1.3.3 School Shootings

**Sources and Measurement**

Data on U.S. school shootings were assembled from www.stoptheshootings.org, Slate, and Wikipedia containing a total of 340 shootings over the period January 2000 to June 2017. School shootings are defined as shootings on school or university premises in which the perpetrator uses a gun. There is considerable variability in the severity of school shootings and many of them do not result in any fatalities. It seems likely that shootings without victims have little impact on the local community while more severe shootings – in terms of fatalities – have larger effects. To account for this, shootings are weighted by the number of fatalities, excluding the perpetrator. As a result, shootings that resulted in no deaths are not considered in the analysis. This selection criterion yields a total of 147 school shootings in the sample.

I then create four alternative indicators of school shootings that differ in the level of risk posed to bystanders. The idea behind this is that shootings (for a given number of fatalities) are more likely to impact public sentiment if individuals feel there is a higher risk that they could be targetted. Based on carefully reading the description of each shooting, I classify them into four categories: (i) total shootings (147 incidents), (ii) shootings that were not motivated by personal dispute[12] (45 incidents), (iii) shootings in which the perpetrator opened fire indiscriminately on a crowd (35 incidents), and (iv) mass shootings in which at least 3 people were killed (17 incidents). These categories are arguably increasing in risk to bystanders. In the sensitivity analysis, I also consider an alternative measure consisting of a dummy for shootings in which at least three people were killed, without weighing these shootings by the number of fatalities. This ensures that results are robust to outliers, i.e. it is not one or two shootings with many fatalities that drive the results.[13]

[12]Examples of shootings motivated by personal dispute include gang-related violence and the perpetrator killing his ex-girlfriend or class teacher after receiving received poor grades in class.

[13]A few mass shootings stand out in our sample with high numbers of deaths: Virginia Tech in April 2007 (32 fatalities and 23 injuries); Sandy Hook, Newtown, Connecticut in December 2012

I map shootings to counties in which the respective schools are located and find that the 147 shootings in our sample occured in 111 different counties, providing substantial cross-sectional variation. Figure A.4 displays the distribution of school shootings and fatalities over time whereas Figure A.5 depicts the distribution of school shooting fatalities across U.S. counties for the sample considered.

**Descriptive Statistics and Exogeneity**

School shootings have occurred on average about once a month in the US since 1970, but the incidence has risen in recent decades, averaging 1.6 such events per month during the sample considered. Contrary to what some might expect, they are primarily an urban phenomenon. In the sample, 73% of shootings occur in counties classified as metropolitan areas.[14] For the purpose of this analysis, this means that the bulk of school shootings occur in highly populated areas with more Michigan survey respondents, given the randomized nature of the sample. Moreover, there is substantial variation in the frequency of shootings across states, where California stands out as an outlier with more than twice the number of shootings as in Florida, the state with second highest number of shootings (see Figure A.7). It seems trivial that we would expect a higher number of shootings to take place in areas with larger populations; what is less trivial are the determinents of shootings per capita. In fact, one might hypothesize that shootings per capita might be the relevant measure impacting individual sentiments. However, I find that it is the total (not per capita) number of school shooting fatalities that affect sentiments with a strong first stage.

There is ample evidence suggesting that the occurance of school shootings is exogenous, i.e. not caused by local economic conditions. First, examining the cross-sectional distribution of shootings across counties, simple t-tests for differences in means do not reject that counties that experience school shootings have equal confidence levels and unemployment rates as those that do not (see Table A.3). On the contrary, counties with shootings have on average (insignificantly) higher confidence and lower unemployment rates, consistent with the fact that most shootings occur in metropolitan areas. Second, examining the distribution

(26 fatalities and 2 injuries); Roseburg, Oregon in October 2015 (9 fatalities and 9 injuries), and Red Lake, Minessota in March 2005 (7 fatalities and 5 injuries). Figure A.6 plots a histogram of mass shooting fatalities.

[14]Note that the U.S. is divided into over 3,000 counties that fully span its territory. The U.S. also contains over 300 metropolitan statistical areas (MSA), defined as a geographical region with a relatively high population density at its core and close economic ties throughout the area. As such, counties may map to zero, one, or more than one metropolitan areas.

of shootings across time, Pappa, Lagerborg, and Ravn (2018) show that U.S. unemployment and the number of school shootings are contemporaneously unrelated over the period 1990-2013, once contagious effects from mass shootings are accounted for.[15] Third, the fact that shootings correlate positively with the various measures of consumer confidence (in both levels and differences), suggests that reverse causality is unlikely (see Table A.4).

Finally, employing panel regressions with both time and county fixed effects, confirms that shootings occur orthogonally to local economic conditions. Using a placebo test, the relationship between current confidence and future shootings is insignificant (see Table A.5 columns 2-3 and 5-6). If drops in confidence led to more shootings, we would instead expect to find a significant negative relationship. Moreover, estimating a linear probability model suggests no impact of lagged unemployment rates on the probability of school shootings (see Table A.6). Taken alltogether, there is no evidence that the distribution of school shootings across counties and time is related to underlying economic conditions.

## 1.4 Methodology and Results

### 1.4.1 Individual-level IV Regressions

To study whether sentiment shocks affect aggregate demand, I first look at their impact on individual consumption attitudes. More specifically, I use a two-stage least squares (2SLS) estimation approach to assess whether exogenous movements in individual confidence, identified using school shootings as an instrument, affect buying attitudes for durable goods, cars, and houses.

In the first stage, I estimate how school shootings affect sentiments for residents in the county of the shooting. I regress the six-month change in individual

[15] Pah et al. (2017) document contemporaneous positive correlation between shootings and unemployment rates and that the arrival rate of shootings varies stepwise over time, with different regimes of high and low shootings. Pappa et al. (2018) show that the different regimes correspond to episodes of contagion from mass shootings, lasting up to three years. Once mass shootings are controlled for, the relationship between school shootings and U.S. unemployment rates disappears. In fact, Towers et al. (2015) find that mass and school shootings are contagious when more than 3 fatalities are involved, and that contagion operates at the national level (e.g. due to widespread media coverage of shootings) but not locally or geospatially (the time between incidents is not significantly correlated to the distance between them). In other words, the higher probability of shootings after mass shooting events can be captured by time fixed effects.

consumer confidence (denoted $S_{i,j,t}$ for *sentiments*) on county-level school shooting fatalities (denoted $Z_{j,t}$) cummulated over those six months, and control for individual and local economic conditions—namely, changes in the individual's personal financial conditions (denoted $Y_{i,j,t}$), county unemployment rates (denoted $UR_{j,t}$), and MSA-level fixed effects (denoted $\alpha_{j \in MSA}$)—as well as aggregate U.S. fundamentals by including time fixed effects (denoted $\alpha_t$). Individual observations are weighted by the household head weights provided in the Michigan Survey and, to correct for heteroskedasticity, standard errors are clustered at the MSA-level. The specification for the first stage can be written as follows:

$$\triangle_6 S_{i,j,t} = \beta \sum_{k=1}^{6} Z_{j,t-k} + \lambda \triangle_6 Y_{i,j,t} + \gamma \triangle_6 UR_{j,t} + \alpha_{j \in MSA} + \alpha_t + u_{i,j,t} \tag{1.1}$$

where i denotes the individual, j the county, t the time period, and $\triangle_6$ denotes the six-month change in the variable that follows.

In the second stage, I estimate the impact of sentiments, measured as the predicted change in confidence from the first stage, on individuals' consumer buying attitudes (denoted $C_{i,j,t}$) for durables, cars, and houses. The specification for the second stage can be written as follows:

$$\triangle_6 C_{i,j,t} = \beta \widehat{\triangle_6 S_{i,j,t}} + \lambda \triangle_6 Y_{i,j,t} + \gamma \triangle_6 UR_{j,t} + \alpha_{j \in MSA} + \alpha_t + \varepsilon_{i,j,t} \tag{1.2}$$

This formulation addresses various estimation issues concerning the measurement of sentiments. Since a subset of individuals respond to the Michigan survey twice, six months apart, considering the change in confidence for a given individual residing in a fixed county[16] eliminates any time-invariant noise. In other words, this cleans confidence indicators of biases associated with individual characteristics—such as age, gender, education, and income—and location fixed effects.

Moreover, this 2SLS specification addresses concerns regarding the endogeneity of sentiments with respect to national, local, and individual economic conditions. Since confidence refers to expectations regarding the national economic outlook, I use fixed effects to capture the component of confidence that represents

[16] Individuals who moved counties during the period are excluded from the sample.

national fundamentals, i.e. economic conditions and other time-varying drivers of confidence at the national-level[17]. Since individual and local economic conditions are important determinants of confidence, I control for changes in personal financial conditions and county unemployment rates, and include MSA-level fixed effects that allow for different location-specific trends in confidence. Finally, remaining endogeneity concerns are taken into account by using school shootings as an instrument for confidence, to identify exogenous variations in individual sentiment.

Validity of school shootings as an instrument for local confidence relies on three identification assumptions. First, the instrument must satisfy the "exclusion restriction". In other words, school shootings should not affect consumer attitudes when confidence is held constant. Since school shootings do not entail significant direct economic costs on the local economy, it is unlikely that they affect economic conditions directly. By this reasoning, I assume that school shootings only impact consumption indirectly through confidence and not through any other channels. Second, the instrument must satisfy "exogeneity". For this, school shootings must be uncorrelated with the error term of the equation of interest. Namely, school shootings should be uncorrelated with any other determinants of the dependent variable. This requires school shootings to occur orthogonally to local economic conditions, thereby mitigating endogeneity concerns of error term correlation with individual economic circumstances. Finally, the instrument must satisfy "relevance". That is, school shootings must be correlated with changes in confidence. Let me define the cummulative school shooting fatalities as $Z_{j,t} = \sum_{k=1}^{6} Z_{j,t-k}$. More formally, the second and third conditions can be expressed as:

$$Corr(\mathbf{Z}_{j,t}, \varepsilon_{i,j,t}) = 0 \tag{1.3}$$

$$Corr(\mathbf{Z}_{j,t}, \triangle_6 S_{i,j,t}) \neq 0 \tag{1.4}$$

Ample evidence suggesting that school shootings are exogenous to prevailing economic conditions was presented in Section 1.3.3. As a final test to claim the validity of my instrument, the strength of the correlation between school shootings and confidence is tested in the first stage of the 2SLS estimation that follows.

[17]Time fixed effects would also capture contagion effects arising from mass shootings (Towers et al. 2015; Pappa et al. 2018).

Table A.7 presents evidence that school shootings significantly affect individual confidence and constitute a strong instrument. On average, per fatality in a school shooting, confidence drops approximately 0.03-0.04 points for individuals residing in the county of the shooting relative to other counties. The magnitude of the coefficient rises slightly for instruments that restrict shootings to those associated with higher risk. Shootings that were not motivated by personal disputes (column 2), those in which the perpetrator opened fire (column 3), and mass shooting incidents in which at least three people died (column 4), reflect incidents in which an innocent bystander has a higher risk of being shot. All measures of shootings pass the Stock and Yogo (2005) weak instrument exclusion test, with F-statistics at or above the rule of thumb value of 10. Hence, the evidence presented in Table A.7 reconfirms results of previous studies (e.g. Clark and Stancanelli 2017; Burns and Crawford 1999) that school shootings affect individual sentiments. Differently from the previous literature, my results establish a direct link between school shootings and confidence that seems to operate through individuals' fear and inability to insure against such events.

Estimates for the second stage show that changes in confidence, instrumented by school shootings, affect individual attitudes for purchasing consumer durables (see Table A.8). A unit fall in confidence, instrumented by school shootings, decreases consumer appetite for durable goods by an almost equivalent amount (0.8-1.0 points) according to the three riskier shooting indicators (columns 2-4), which also correpond to the strongest instruments (higher F-statistics in the first stage).[18] These point estimates can also be interpreted as elasticities in units of standard deviation since confidence and buying attitudes have very similar standard deviations (see summary statistics in Table A.2). By contrast, no significant effect of sentiments is found for large ticket items such as car and house purchases (see Tables A.9 and A.10). These results indicate that, at the individual level, shocks to confidence may, at the least, propagate through changes in the consumption behavior for smaller durable items. Moreover, they contrast the "null result" documented by Mian et al. (2015) where sentiment regarding government economic policy is found to have no effect on consumer buying attitudes and spending on durables and autos at the county-level (using both OLS and IV). Instead, I find that changes in sentiment concerning national output growth significantly alter consumer buying attitudes. Thus, to the extent that consumer buying attitudes

[18] When I consider heterogeneous effects in Section **??**, a significant effect on durables is also found for total shootings as the instrument.

may translate to actual consumption, my findings suggest that sentiment shocks can have real effects on the economy.[19]

Finally, Table A.11 presents results using ordinary least squares. OLS regression estimates reveal that a rise in confidence is associated with increases in consumer buying attitudes for durables, cars, and houses. Since higher income individuals have both higher confidence and appetite for consumption, a positive relationship between confidence and consumption could be driven by reverse causality (individuals' economic resources rather than sentiments). By estimating the relationship in differences, I eliminate effects stemming from time-invariant economic conditions (columns 1-3). A unit increase in confidence translates to very small increases in consumer buying appetite (respectively 0.06 for durables, 0.05 for cars, and 0.03 for houses). Yet, changes in fundamentals could drive the results in differences, e.g. an individual getting a job promotion or a new factory reducing local unemployment would raise both confidence and consumer buying appetite. As a first attempt to deal with this issue, I ensure that results are insensitive to changes in individual and county economic conditions. Point estimates remain stable when controlling for changes in personal finances, county unemployment rates, and MSA fixed effects which allow for different MSA trends in consumer buying attitudes (columns 4-6). Nevertheless, the survey response to whether personal finances improved, worsened, or remained unchanged over the past year, is admittedly an imperfect attempt to control for changes in individuals' economic fundamentals. To correct for biases stemming from this potential endogeneity concern, I have turned to an instrumental variable estimation approach.

Indeed the results presented in Table A.11 highlight the importance of controlling for endogeneity in confidence. Use of my proposed instrument to identify exogenous variations in sentiments is shown to alter results not only quantitatively but also qualitatively. According to OLS estimations, variations in confidence comove with consumer buying appetite for larger items such as cars and houses. Instead, using my instrument to identify exogenous changes in sentiments, I observe that causal effects are limited to smaller consumer purchases such as durable goods. Finally, another important reason to instrument for confidence is measurement error. Since true consumer sentiment is unobervable, and the proxy used

[19] Unfortunately, the county-level data on credit card spending and auto purchases used by Mian et al (2015) is not publicly available and can be purchased only at a sizeable fee. As such, I cannot test whether the impact of sentiments on buying attitudes translates to actual purchases. Yet, Mian et al (2015) find no impact on both buying attitudes and actual consumption, so my findings differ from this null result.

from Michigan survey responses takes discrete values from 1 to 5, measurement error is bound to be large. As a result, estimation via OLS suffers from (downward) attenuation bias, resulting from large variance in the regressor, a problem that is magnified when the regressor is measured in differences. In fact, OLS estimates of the effect of sentiments on buying attitudes for durables are an order of magnitude smaller than the corresponding IV estimates.[20]

### 1.4.2 County-level IV Regressions

While the individual-level analysis relates sentiments to consumer buying attitudes, it cannot measure impacts on actual consumption due to unavailable data. Therefore, to measure real effects of sentiment shocks, I turn to analysis at the county-level. Insofar as sentiment shocks emulate a demand shock, pessimism would lead to a drop in consumption and output and a rise in unemployment. Constrained by the indicators available at monthly frequency for U.S. counties, the analysis focuses on unemployment rates, which can be thought of as proxying economic activity more generally. The idea is to study the dynamic evolution of county unemployment rates in response to exogenous variations in sentiment.

One issue that emerges is that the small number of survey interviews per county-month can lead to a very noisy measure of county-level confidence. I address this by measuring county-level changes in sentiment ($\overline{S}_{j,t}$) as the average change in confidence for interviewees living in a given county, who respond to the Michigan survey twice, thereby removing any time-invariant biases attributable to individual characteristics and location (fixed effects). I further reduce noise stemming from changes in respondents' economic conditions by controlling for their average change in personal finances ($\overline{Y}_{j,t}$). Including time fixed effects, thought of as capturing aggregate U.S. fundamentals common to all individuals, the residual component of confidence can, as before, be attributed to sentiments that are orthogonal to national economic fundamentals.

I deal with potential concerns about reverse causality, whereby changes in local economic conditions may affect changes in sentiments, in two ways. First, I control for local economic conditions by including 12 lags of county unemployment rates as well as location fixed effects and trends (at the MSA level). Still, it is

[20] A similar order of magnitude difference between OLS and IV was reported by Mian et al. (2015) for county-level consumption of cars and durables and Benhabib and Spiegel (2016) for state-level GDP growth.

possible that, as an example, news of a factory closing in a county reduces confidence among its residents. Following the same logic as in the previous section, I use a 2SLS estimation in order to identify exogenous fluctuations in sentiments.

In the first stage, exogenous movements in sentiments are identified by my instrument: school shootings. The six-month county-level change in confidence is regressed on cummulative shooting fatalities over the past six months, 12 monthly lags of the county unemployment rate, a time fixed effect, and MSA-level fixed effects and trends.[21] Counties are weighted by their population (using data obtained from the U.S. Census Bureau for the year 2000) which, by the nature of the RDD design, is similar to weighing counties by their total number of interviews as these two variables are highly correlated (correlation coefficient 0.96). The following specification is estimated where upper bars denote average responses for interviewees in county j at time t:

$$\triangle_6 \overline{S}_{j,t} = \beta \sum_{k=1}^{6} Z_{j,t-k} + \lambda \triangle_6 \overline{Y}_{j,t} + \sum_{k=1}^{12} \theta_k UR_{j,t-k} + \alpha_{j \in MSA} + \gamma_{j \in MSA} t + \alpha_t + \varepsilon_{j,t} \tag{1.5}$$

Next, the second stage measures the impact of predicted confidence from the first stage on county-level unemployment rates at different time horizons. I use local projection methods (Jordà, 2005) with a two-stage instrumental variable approach to estimate impulse responses that are analogous to direct forecasting. Control variables are the same as the first stage: time fixed effects capture aggregate US fundamentals; MSA-specific fixed effects and trends and lagged county unemployment rates capture recent local dynamics in the business cycle; the average change in respondents' personal finances reduces noise in county confidence. The local projection takes the following form and is estimated using a 2SLS procedure for each projected horizon $h \geq 0$, reflecting the varying timing of the dependent variable, where the sequence of estimated coefficients $\beta^{(h)}$ delineate the impulse response function of unemployment to the sentiment shock:

$$UR_{j,t+h} = \beta^{(h)} \widehat{\triangle_6 \overline{S}_{j,t}} + \lambda^{(h)} \triangle_6 \overline{Y}_{j,t} + \sum_{k=1}^{12} \theta_k^{(h)} UR_{j,t-k} + \alpha_{j \in MSA}^{(h)} + \gamma_{j \in MSA}^{(h)} t + \alpha_t^{(h)} + \varepsilon_{j,t+h}^{(h)} \tag{1.6}$$

[21] Since it may be the level of confidence, not just the change, that matters for unemployment, I also estimate a specification in which I control for the initial level of confidence six months ago. Results are robust whether I control for initial confidence or not.

Note that the error term will be serially correlated for all horizons h>0, since it is a moving average of the forecast errors from t to t+h, requiring a correction for standard errors.[22] I use cluster-robust standard errors at the state level, which assumes errors are independent across states but allows them to be correlated within states, making standard error estimators robust to arbitrary heteroskedasticity and within-cluster autocorrelation. This relies on the assumption that the number of clusters, rather than just the number of observations, goes to infinity. Kézdi (2005) demonstrates that 50 clusters (with roughly equal cluster sizes) is close enough to infinity for accurate inference, validating the choice of clustering by U.S. states. As a robustness check in Section 1.5, I show that results are insensitive to two-way clustering of standard errors by both states and time periods, which accounts for arbitrary autocorrelation within states and contemporaneous correlation across states (clustering on time).

An additional identification assumption is required in the context of local projection IV. Because of the dynamic nature of the macroeconometric problem, instrument exogeneity entails a strong "lag exogeneity" requirement that the instrument be uncorrelated with lead and lagged shocks, after including control variables. Lead exogeneity follows from the definition of shocks as unanticipated structural disturbances; lag exogeneity requires that school shootings be unforecastable in a regression of the shooting instrument on lags of unemployment.[23] Evidence that past unemployment does not predict school shootings was presented in Table A.6. This identification assumption can be expressed more generally as:

$$Corr(\mathbf{Z}_{j,t}, \varepsilon_{i,j,t+s}) = 0 \text{ for } s \neq 0 \tag{1.7}$$

Table A.12 shows that school shootings again constitute a strong instrument for county-level confidence. Similarly to the first-stage estimates of the individual-level regressions, each of the shooting indicators used as instruments has a significant negative impact on confidence and an instrument exclusion F-statistic exceeding 10. At the county level, estimates are slightly higher, on average: per fatality in a school shooting confidence drops approximately by 0.05-0.06 points for the average respondent in the county of the shooting, indicating that aggregate

[22]Notice that in our large T context (210 time periods for each county in the panel), the so-called Nickell (1981) bias for the coefficients on lagged dependent variables, in dynamic panel regressions with fixed effects when T is small and N is large, is bound to be negligible.

[23]Even if the lag exogeneity condition fails, the endogeneity problem can potentially be addressed by including additional regressors that control for lagged shocks.

responses at the county level do not alter the mechanism through which school shootings propagate to confidence.

Figures A.8 and A.9 plot the impulse response function of unemployment to a negative confidence shock, instrumented by county school shootings, considering the least and most restrictive shooting indicators respectively. In both cases, the point estimates indicate that an exogenous drop in confidence leads to an increase in unemployment rates lasting up to 1.5 years later. A unit fall in the confidence indicator is found to raise the unemployment rate by a maximum of 0.3 percentage points when I consider all school shootings as instruments and 0.5 percentage points when I restrict the sample to mass shootings. Expressed differently, a one standard deviation fall in confidence (1.66 points) raises unemployment rates by a maximum of 0.5 to 0.8 percentage points, for roughly betweeen one-half to one-and-a-half years later. The magnitude of the impact on unemployment rates is sizeable. During the Great Recession, the U.S. unemployment rate rose from 4.6 percent in March 2007 to 9.9 percent in January 2010, marking the steepest increase since the 1930's Great Depression. By comparison, a large autonomous drop in confidence, by the maximum of four units on the confidence scale, can translate to an increase in county unemployment rates by 2 percentage points, amounting to three-fourths of the increase during the Great Recession.

The estimated specification has the common problem of large standard errors inherent to local projections IV. Confidence intervals are shown both at the 68 and 95 percent, represented by the shaded areas depicting 1 and 2 standard error confidence bands. This means that the rise in unemployment rates is, for a large part, significant using 68 percent confidence bands. However, significance considering the 95 percent bands is obtained for a limited horizon when mass shootings are used as instruments. Very large standard errors are a by-product of the large number of coefficients to be estimated using local projections since all parameters are re-estimated for each horizon in time, compared to vector autoregressions where all parameters are estimated only once. A promising new methodology called "smooth local projections" (Barnichon and Brownlees, 2017), proposes to reduce standard errors by assuming that impulse responses are a smooth function of the horizon, thereby reducing the dimensionality of the coefficients to be estimated[24].

The county-level analysis reveals that sentiment shocks have sizeable real effects on unemployment that are short-lived, lasting approximately 1 year. This

[24]This paper is currently under revision and codes on how to estimate standard errors will be made available shortly.

suggests that sentiment shocks can trigger substantial macroeconomic fluctuations in the short-run. To the extent that sentiments impact unemployment, we can also expect effects to extend to other macroeconomic variables, such as consumption and output, for which we do not have data at the county-level. That sentiment shocks can have sizeable short-term real effects is in line with findings by Benhabib and Spiegel (2016), that suggest confidence has large effects on output growth at the state-level, although they document a more persistent effect that lasts up to three years. Finally, the result that a pessimistic outlook regarding the U.S. economy worsens employment conditions locally resonates He (2017), who documents that higher county exposure to negative news regarding the national economy was associated with more aggravated increases in county unemployment during the Great Recession.

Figure A.10 plots the impulse response function to a confidence shock estimated using OLS, showing smaller effects on unemployment that are longer-lived. The size of the effect using OLS is again one order of magnitude smaller than using IV (a result that is in line with Mian et al. 2015 and Benhabib and Spiegel 2016). The estimated magnitude of the impact is small whereby following a 1-point drop in the confidence index, the unemployment rate reaches a maximum increase of 0.015 percentage points. In other words, a one standard deviation fall in confidence (1.66 points) is associated with a 0.025 percentage point rise in the unemployment rate. Moreover, a drop in confidence is associated with higher unemployment rates for approximately 3 years.

Again we observe that using an instrument is important to deal with measurement error in confidence, which would cause attenuation bias in OLS estimates. Also controlling for endogeneity is qualitatively important for determining whether sentiment shocks have real effects. Employing OLS, the estimated effects on unemployment are smaller, but more significant for a longer period; employing IV, effects on unemployment are larger in magnitude but for a shorter horizon, and this comes at the expense of losing precision. These results contrast Benhabib and Spiegel (2016), who document that effects of sentiment shocks on state output growth are qualitatively consistent for OLS and IV, in both cases longer-lasting, up to 3 years. Using a different instrument, I show that once endogeneity is controlled for, the effect on unemployment rates reduces from 3 years to approximately 1 year.

## 1.5 Robustness Checks

This section performs a series of sensitivity tests to verify the robustness of my findings. Given the novelty of using school shootings as an instrument for confidence, I first present additional evidence confirming that shootings give rise to significant drops in confidence. Results are robust to considering: different regression specifications, additional shootings in the sample, alternative confidence indicators, and an enlarged treated sample by studying the impact of shootings on larger geographic areas. Finally, at the end of this section, I show that results in the second stage are also largely robust to these modifications. These sensitivity analyses confirm the effects of sentiment shocks, identified using school shootings as an instrument, on individual consumer behavior and county unemployment rates.

### 1.5.1 Alternative Specifications

The negative impact of school shootings on local sentiment regarding the national economic outlook is robust to numerous variations in the baseline specification. At the individual level, Table A.13 shows that first-stage estimates are insensitive to: including controls for lagged confidence and personal finances, clustering standard errors by states instead of MSAs, and giving equal weights to all observations. Inclusion of initial values are meant to account for possible mean reversion since, for example, if confidence is initially at its lowest possible value of 1, it cannot fall further after a shooting takes place. In fact, there is evidence of mean reversion in confidence whereby a higher initial confidence is associated with a subsequent drop. Improvements in personal finances, both current and lagged, are associated with increases in confidence. Clustering at state-level assumes that errors are uncorrelated across states, while recognizing that they could be correlated across MSAs within the same state. Finally, the result that school shootings reduce local confidence does not hinge upon weights assigned to household heads in the Michigan survey.

At the county level, first-stage estimates are similarly insensitive to: (i) county or MSA fixed effects, (ii) allowing or not for MSA-specific trends, (iii) alternative clustering of standard errors by states or MSAs, and (iv) weighing observations by the number of interviews in the county instead of population.[25] Table A.14 shows that county-level first stage results are robust to controlling for initial levels of confidence and personal finances, county fixed effects, excluding MSA-specific trends, and clustering standard errors according to MSAs. Results are preserved when the initial level of confidence is included to account for mean reversion and allow unemployment dynamics to depend on the level, not only the change, in confidence. They are also preserved under these alternative controls for local economic conditions, namely different location fixed effects, exclusion of location-specific trends, and standard error clustering at a broader geographic area. Finally, Table A.15 shows that school shootings also reduce county confidence when observations are weighted by the number of interviews in the county instead of population, although significance and instrument strength is somewhat reduced.

### 1.5.2 Shooting Outliers

I also verify robustness of instrument strength to shooting outliers, to ensure that it is not just one large school shooting event that is driving results. First, I consider an alternative instrument: a dummy variable that takes value 1 for mass shootings with at least 3 fatalities. Table A.16 (column 1) confirms that mass shooting events, even without being weighed by fatalities, generate a significant drop in county-level confidence about nationwide economic growth prospects, which is orthogonal to fundamentals that are captured by time fixed effects. This is robust to including controls for respondents' personal finances and local economic conditions (column 2) as well as for initial confidence that captures mean reversion (column 3). Instrument strength remains high with exclusion F-statistics above 10.

Second, I check sensitivity to including additional mass shootings events in the sample. In fact, the deadliest school shooting during the time period considered—the Virginia Tech massacre in which 32 people died in Blacksburg, Virginia on April 16, 2007—is excluded from the baseline analysis since no interviewee in Montgomery County responded to the Michigan survey both before and after

[25] Results are not reported for each of these cases on account of space, but are avaiable from the author upon request.

the shooting. However, I can include this shooting by considering interviews for different individuals. In fact, this would only make results stronger since confidence drops from 5 to 1 for the individuals who replied six months apart, before and after the Virginia Tech massacre. Table A.17 shows that individual-level results are robust to a placebo test that assumes these responses pertain to the same individual, thereby including the deadliest shooting incident in the sample.

I can apply this exercise more generally at the county-level by considering all interviewee responses six months apart, meaning that two thirds of responses in the county still pertain to a constant individual. This is already a large improvement in controlling for noise (stemming from respondent-specific biases) in local county confidence compared to e.g. Mian et al. (2015) who do not consider this six-month change, meaning that the full sample of interviewees changes each period. Table A.18 shows that results remain robust to including all interviews in the sample in constructing average county confidence. By doing this, ten more school shootings are included in the sample.

### 1.5.3 Alternative Confidence indicators

Given that school shootings affect sentiments regarding nationwide economic growth over the medium run, we may stipulate that they could affect sentiments similarly for short-term growth. While this may be a less relevant measure to study sentiments, since confidence about the nearer-term outlook will relate more to current fundamentals of the economy, I am interested in using this alternative confidence indicator to verify whether results are robust. I consider the following question in the Michigan survey (BEXP): "*And how about a year from now, do you expect that in the country as a whole business conditions will be better, or worse than they are at present, or just about the same?*" where responses can take values 1, 3, and 5, which I order to be increasing in optimism. Table A.19 shows that school shootings also cause a significant drop in sentiments concerning national business conditions one year ahead.[26] In other words, school shootings are shown to

[26] Another survey question relating to the short-term national outlook asks about business conditions within the next 12 months (BUS12). Precisely, it asks "*Now turning to business conditions in the country as a whole--do you think that during the next 12 months we'll have good times financially, or bad times, or what?*" The wording "within the next 12 months" suggests a period-average rather than period-end estimate, and that it possibly incorporates forecasts in an even shorter term horizon than "a year from now". This question is identical to the baseline measure I use for confidence where the only difference regards the time horizon of 12 months rather than 5 years. Using this

be a strong instrument for local sentiments not only regarding national economic growth over a 5 year period but also 1 year ahead.

Next, I contrast results to considering alternative commonly-used measures of confidence such as broad consumer sentiment (ICS) and its two subcomponents: sentiment over current economic conditions (ICC) and consumer expectations over the future (ICE). I find that school shootings are associated with a drop in overall consumer sentiment for two of the shooting instruments: shootings not motivated by personal disputes and mass shootings (see Table A.20). However, disaggregating between the two subcomponents, I observe that this effect is driven by the expectational part. I find that school shootings affect ICE (see Table A.21), which reflects expectations relating to the national economic outlook (our baseline measure of confidence) as well as future improvements in personal finances. The endogeneity issue inherent in this expectational component of overall consumer confidence, is that it may relate not only to sentiments but also news about average personal financial situations. By contrast, shootings have no significant effect on the current component of consumer confidence, which relates to current durables purchasing attitudes and improvements in personal finances relative to 1 year ago (see Table A.22)[27]. As such, an increase in this measure of confidence directly reflects improvements in both individual and local economic conditions, making the endogeneity issue very accute. That shootings are unrelated to current economic conditions is in fact encouraging, since the type of sentiment shock being studied is meant to be orthogonal to fundamentals.

### 1.5.4 Larger Geographic Areas

The analysis so far allows for common effects on consumer confidence throughout U.S. counties through the presence of time fixed effects, but otherwise assumes that school shootings impact only on confidence for residents of the local county. In order to test for robustness of results to increasing the size of the treated sample, I study whether shootings affect confidence in larger geographic areas that encompass neighboring counties. I construct an MSA-level measure of school shootings, allowing these events to affect confidence in all counties pertaining to the MSA where the shooting took place, and restrict the estimation sample only to MSAs.

measure of confidence, school shootings are found to have a substantially weaker impact on sentiments.

[27]Note that here I do not control for improved personal finances since this is one of the two indicators that makes up ICC.

This increases the treated sample substantially by a multiple of 3 to 6 depending on the shooting indicator considered. The first stage remains robust, i.e. shootings affect confidence for the MSA where they took place (see Table A.23).

Next, I study whether the effects of shootings on confidence spillover to other counties in the same MSA (see Table A.24). I find evidence of spillover effects only for mass shootings (see column 4). While the impact on sentiments is stronger for the county where the shooting took place, other counties in the same MSA are also negatively and significantly impacted. That the effect of shootings can spillover to neighbor counties, does not seem to stem from network effects. If instead network effects were at play, drops in confidence stemming from all types of shootings in other counties within your MSA, would directly reduce your confidence. Rather, these findings seem to suggest an important role played by media coverage or word of mouth reaching other counties only for deadlier shooting events. Moreover, regressing changes in county confidence on time and county fixed effects and changes in confidence in other counties pertaining to the same MSA, this last regressor is insignificant, suggesting that confidence in one county is not directly affected by changes in confidence in neighbor counties (see Table A.25).

### 1.5.5 Robustness of the Second Stage

Having demonstated that local confidence robustly drops following school shootings for a myriad of sensitivity tests, I also investigate the stability of second stage results. At the individual level, Table A.26 displays 2SLS estimates for selected sensitivity tests using mass shooting fatalities as the instrument for confidence, given its strength in the first stage and significant effects on appetite for household durables in the second stage. Columns (1) and (2) respectively present first and second stage results for an altered specification that allows for initial values of confidence and personal finances, clustering of standard errors at state rather than MSA level, and gives equal weights to all survey respondents. Mass shooting fatalities are shown to reduce confidence with a strong first stage which, in turn, significantly reduces appetite for durables. Columns (3) and (4) present first and second stage results for a specification in which the Virginia Tech school shooting is included in the sample by considering survey responses across different individuals. Mass shooting fatalities are again shown to reduce confidence with a very strong first stage and this, in turn, significantly reduces durables purchasing attitudes. Columns (5) and (6) show results for a specification in which condience regards the 1-year ahead economic outlook (rather than the baseline 5-year horizon). The first stage instrument weakens slightly with an exclusion F-statistic of 6 in the first stage, but the second stage remains signficiant. Finally, columns (7) and (8) present results that shootings impact confidence at the MSA-level, although this does not translate to a significant change in buying attitudes for durables in the greater MSA area.[28] Overall, these results show that second stage results, whereby sentiments impact individual attitudes towards purchasing consumer durables, are largely robust to a variety of sensitivity checks.

At the county level, I plot the response of unemployment to negative confidence shocks, considering a variety of sensitivity tests. Figure A.11 shows robustness to the following alterations to the baseline specification: two-way clustering of standard errors by states as well as time periods, inclusion of initial conditions, and exclusion of MSA trends (left panel) combined with county instead of MSA fixed effects (right panel). Figure A.12 ensures robustness to outlier shootings with many fatalities, where the instrument constitutes a dummy for mass shootings. Figure A.13 increases the sample of treatment counties that experience school shootings by considering all survey respondents, not only those interviewed twice. Figure A.14 considers a shock to confidence regarding the economy one year ahead instead of a five year horizon. And finally, Figure A.15 considers two instruments for confidence, own county shootings as well as shootings in other counties within the MSA. In each of these robustness checks, negative confidence shocks generate increases in unemployment rates that are significant considering a 68 percent confidence band.

## 1.6 Heterogeneous Effects

The way shootings impact on individual and couny-level sentiment can depend on characteristics of the individual and the surrounding environment. Some individuals and counties may be more impacted than others in response to the same school shooting incident. For example, it may be that some individual traits make them generally more emotional than others or, for example, that living in an area with stronger emotional connection among residents and less of a gun culture, causes individuals to react more to such violent events. In other words, sentiment

[28] When I include two shooting instruments – mass shootings in the own county as well as other counties in the same MSA – the positive effect of confidence on consumer durables purchasing attitudes is almost significant, with a significance level of 11%.

shocks can have a *cultural* component. In order to study heterogeneous effects, I allow for an interaction effect in the IV estimation between shootings and: (i) individual characteristics ($X_i$) such as gender, age, education, and income, and (ii) county-level characteristics ($X_j$). It may also be that for the same change in sentiment, individuals react differently in terms of consumption behavior. To investigate this hypothesis, I also study heterogeneous effects of sentiments by allowing for an interaction effect between confidence and individual characteristics using OLS estimates.

### 1.6.1 Heterogeneous Effects in OLS

Analogous to how individual characteristics can influence their confidence (as seen in section 1.3.1), these same characteristics may also influence how individuals react to sentiment shocks. More pessimistic beliefs about the national economy could affect consumption habits for some individuals more than others. This can be tested by interacting changes in confidence with individual characteristics, and looking at whether these interaction effects matter for individual consumption attitudes for durables, cars, and houses. OLS regression estimates presented in Table A.27 reveal that increases in confidence have a larger impact on durables buying attitudes for females and higher income quintiles (column 1).[29] No significant evidence of heterogeneous effects is observed for buying attitudes regarding cars and houses (columns 2 and 3).

That the effect of sentiment shocks on durables purchases is stronger for higher income quintiles, at first thought, may appear inconsistent with theories of credit constrained households being hand-to-mouth. Yet this result resonates with findings by Souleles (1999) that document excess sensitivity of durables consumption to income tax refunds (i.e. predictable and transitory income receipts that do not increase expected permanent income) with a significantly higher marginal propensity to consume especially among income unconstrained households. Souleles (1999) interprets this as evidence contradicting the lifecycle or permanent income theory of consumption (due to the predictable and transitory nature of income tax refunds) and a puzzling result for liquid households "who need not tie their durables purchases to the arrival of a refund check". In contrast, an

[29]Individual characteristics are included both independently and interacted with changes in sentiment. Other controls include: changes in personal finances and county unemployment rates, time fixed effects, and MSA fixed effects.

increase in sentiments about national economic conditions over the medium-term horizon, as studied here, would raise expectations regarding permanent income, thereby making increases in consumption consistent with lifecycle and permanent income theories. Furthermore, to the extent that these sentiment shocks are unrelated to fundamentals, higher optimism does not mean credit constraints are actually relieved for lower income households, making results less puzzling. Even if constrained households expect a boost in their permanent income, being credit contrained would prevent them from consuming more. Hand-to-mouth households, either poor or wealthy but with sizeable amounts of illiquid assets (Kaplan and Violante, 2014), should respond little to news of an increase in permanent income.[30] Instead, unconstrained households (wealthy non hand-to-mouth) expecting a permanent income boost could more easily respond by increasing consmption.

### 1.6.2 Heterogeneous Effects in IV

**Individual Level**

There could also be heterogeneity in how individual sentiments respond to school shooting incidents. Testing this hypothesis is akin to exploring whether an interaction term between school shootings and individual characteristics affects the response of sentiments. I find that females and individuals with higher education and income become relatively more pessimistic as a result of school shootings, while there is no difference in how individuals of different ages react to school shootings (see Table A.28). Note that while the interaction term for females is insignificant for total shootings, it is instead significant for all other shooting instruments.[31] That females and higher education individuals are impacted more strongly is consistent with findings in an event study by Clark and Stancanelli (2017) of two recent massacres in the US. They observe that the Boston Marathon Bombing lowered subjective well-being for individuals across the U.S. especially among women, whereas the Sandy Hook school shooting induced increased feelings of meaningfulness especially strong among the highly educated. The stonger reaction among higher income/education individuals could be because they have

[30] Still, wealthy hand-to-mouth households should display larger marginal propensities to consume than their poor counterparts, as their higher wealth means they have higher desired target consumption (e.g. Kaplan and Violante, 2014).

[31] Regression results available upon request.

the highest confidence to begin with, so their confidence levels are in fact converging to that of individuals with lower education and income. In other words, they have “more to lose”.

Given that sentiments of women and higher income quintiles react more to shootings, and precisely these individuals have a seemingly more elastic response of durables consumption to a given change in sentiment (aforementioned OLS result), this may magnify the effect on consumption. To allow for this, I consider the interaction of school shootings with individual characteristics as additional instruments for confidence in the two-stage least squares estimation. In the first stage, interacting shootings with a female dummy and income quintiles improves instrument strength for total shootings, as measured by the instrument exclusion F statisitic (see Table A.29 column 1). This, in turn, also increases the significance and magnitude of the effect of confidence on durables consumption in the second stage (column 2). Thus we see that taking heterogeneous effects into account can improve instrument strength and magnify the impact of shooting-induced sentiment shocks on consumption. Coefficient magnitudes and significance remain highly robust for all other shooting instruments (columns 3-8).

**County Level**

Heterogeneity in how individual sentiments respond to school shootings may also relate to their surroundings, i.e. county characteristics. For example, we might expect a different reaction to shootings depending on local gun culture and the frequency of violent events, or whether the shooting occured in a city or rural area. Counties with a small population or in which residents are more closely connected might be expected to react more strongly. To evaluate questions of this sort, I include an interaction term between school shootings and several indicators measuring county characteristics – such as local political and gun culture and urban culture – in the first stage regression for sentiments.

Identifying a causal relationship is tricky since the types of county characteristics considered here are time-invariant and are likely to correlate with other omitted characteristics. To claim causality, one would need time-variation in these variables and, ideally, exogenous instruments. As a result, this analysis should be thought of merely as descriptive correlations between county characteristics and the reaction of sentiments to shootings.

I gather data on local political and gun culture from a variety of sources. County-level data on political affiliation, measured as the average share of votes for the republican party in three presidential elections (2008, 2012, and 2016), were obtained from the Guardian and townhall.com. County-level data on political ideology, capturing constituents' mean policy preferences, increasing in more conservative or "right-wing" ideals on various issues were obtained from Tausanovitch and Warshaw (2013).[32] I also obtain two indicators relating to state gun laws, in particular, a dummy for whether gun background checks are required (source: http://gunlawscorecard.org) and a state score between 1 and 9 based on both background check requirements and restrictions on carrying guns in public, increasing in lax gun control (source: Law Center to Prevent Gun Violence). State data on percentage prevalence estimates of adults with loaded household firearms were obtained from Okoro et al. (2005).

I also gather county-level data on various measures of urban culture. An indicator on rurality and remoteness, taking discrete values 1 to 9 that distinguishes metro areas by population and non-metro areas by urbanization and adjacency to a metro area, was obtained from the US Department of Agriculture (USDA). A measure of creative employment, measured as the percent of population employed in occupations that require "creative thinking" was also obtained from the USDA. Finally, county average net migration rates during the 1990s, measured as the difference between immigrants and emigrants relative to population, was obtained from www.netmigration.wisc.edu. Correlation coefficients across different county characteristics are reported in Table A.30.

Results on how sentiments respond differently to shootings depending on local political and gun culture are presented in Table A.31. Sentiments are found to respond less to school shootings in counties with more republican-leaning preferences (column 1). The interaction of shootings with the Tausanovitch and Warshaw (2013) measure of conservative political ideology is insignificant but barely so, with a p-value of 0.101 (column 2). Individual sentiments also react less to shootings in counties with stronger pro-gun culture as measured by state-level policies regarding relaxed firearm purchase background check requirements (column 3), an indicator increasing in lax gun cuntrol (column 4), and percentage of households with loaded firearms (column 5). Political and gun culture are highly interrelated. According to SurveyMonkey data, gun-owning households (roughly a third in America) backed Mr. Trump by 63 percent to 31 percent, while households without guns backed Mrs. Clinton, by 65 percent to 30 percent in the 2016

[32]This measure was constructed by combining over 275,000 individual-level survey responses for binary choices regarding a range of policy preferences. It takes values in the range (-1,1) explaining why the average marginal effect of shootings is significantly negative for liberals despite the coefficient on total shootings turning positive.

presidential election. Quoting the title of a recent New York Times article "nothing divides voters like owning a gun".[33]

Table A.32 explores how shootings have heterogeneous effects on sentiments according to county characteristics relating to urban culture. Sentiments are found to respond less to school shootings in counties that are more rural and remote (column 1), counties that experienced higher net migration rates (column 2), and counties that have a higher share of employment in creative activities (column 3). Interestingly, despite effects going in the same direction, these last two factors correlate negatively with rurality and remoteness, as they are predominantly urban phenomena. Yet findings here are descriptive correlations; I cannot test for a causal relationship nor why these effects are found. One can think of different possible explanations. Individuals might be less sensitive in areas characterized by greater "emotional distance" between individuals. This could, for example, be the case for rural areas characterized by low population density or counties where a high share of recent immigrants retain stronger emotional connection with their place of origin, rather than location of residence. Individuals might also have more stable confidence regarding the national economic outlook in more "resilient economies". Areas attracting large arrivals of migrants may be doing so precisely because their economies are more robust and growing faster. There is also a recent literature (e.g. De Propris, 2013) highlighting the resilient dynamism of the creative economy. I remain agnostic as to the rationale behind these correlations.

Finally, I investigate how the sensitivity of sentiments and frequency of shootings interact with county population. In fact, it seems that places with a higher frequency of shootings per capita, i.e. where shootings are more common, react less to shootings. Table A.33 shows how shootings and shootings per capita correlate with state gun control and metropolitan/high population density areas. Shootings, at first sight, are more likely to occur in: (i) states with stricter gun laws (column 1), and (ii) urban/high population density areas (column 3). However, controlling for county population, shootings are more likely to occur in: (i) states with lax gun laws (column 2), and (ii) less densely populated, in other words more remote, areas (columns 4 and 5). These results are preserved when we include both gun policy and population density together (column 6). Confidence in such counties, as shown earlier, is less sensitive to school shootings. This further

[33]This article was written by Nate Cohn and Kevin Quealy published on October 5, 2017 and is available online at:
https://www.nytimes.com/interactive/2017/10/05/upshot/gun-ownership-partisan-divide.html.

supports the idea that the relationship between school shootings and confidence seems to operate through individuals' fear and inability to insure against such events.

## 1.7 Conclusion

There is scant empirical evidence on the causal role of confidence in driving macroeconomic fluctuations. Above all, identifying this causal relationship is problematic due to strong reverse causality, an issue very few studies have made serious attempts to correct. The main estimation challenge is to identify autonomous changes in confidence that are unrelated to economic fundamentals.

To this end, I exploit school shootings as a novel natural experiment to proxy for sentiment shocks. I adopt an instrumental variable two-stage least squares approach, in which school shootings are used to instrument for autonomous fluctuations in consumer optimism regarding national economic growth. School shooting incidents are shown to be exogenous (i.e. orthogonal to local economic conditions) and relevant (i.e. lead to significant drops in individual and county-level confidence) with a very strong first stage. Using this instrument to identify exogenous movements in sentiments, I find that sentiment shocks resemble aggregate demand shocks and have real effects. Drops in sentiment reduce individual consumer appetite for purchasing durable goods. Employing local projection methods to estimate impulse responses, negative sentiment shocks are found to raise county unemployment rates, where the effects are sizeable but short-lived, lasting approximately one year. Using an instrument is important to account for measurement error and endogeneity. By contrast, simple OLS yields smaller coefficient estimates and distorts real effects: the impact on buying attitudes extends to larger items (cars and houses) and effects on unemployment extend for longer-periods (3 years). These results survive a wide array of sensitivity tests.

This paper contributes to the on-going debate among macroeconomists on the relevance of animal spirits in explaining business cycles. Its findings should be interpreted as empirical evidence that animal spirit shocks can drive macroeconomic fluctuations, supporting models of belief or expectation-driven business cycles. That public confidence impacts the economy has various implications that can be extended to forecasters, policymakers, and media outlets.

A large gap remains for future work exploring the causal role of confidence. The field has so far found very few natural experiments to study this empirical question, welcoming new creative ideas for additional instruments that can be used to identify exogenous fluctuations in confidence. The literature would likewise benefit from analysis looking at other economic outcomes to further uncover the macroeconomic implications of these shocks. A better understanding of sentiment shocks in terms of the nature, size and duration of their impact as well as historical relevance in driving business cycle fluctuations, is important in order to design appropriate policy responses.

# Chapter 2

# Does Economic Security Really Impact on Gun Violence at U.S. Schools?

*Joint with Evi Pappa and Morten Ravn*

## 2.1 Introduction

Much research examines the impact of unemployment on crime. The consensus view is that while there is a crime-unemployment link, it is weak for most types of crimes and inexistent for others including violent crime and murder (Levitt 2004, Corman and Corman 2005). Empirical studies typically find a statistically insignificant or even negative impact of unemployment on murder rates. Furthermore, unemployment correlates negatively with most measures of school violence (Table B.22).

Pah et al. (2017), by contrast, conclude that higher unemployment (and economic insecurity in general) *causes* increased risk of school shootings. We argue that the estimated correlation between unemployment and school shootings does not reflect a causal relationship but derives from omitted variables, such as lack of control for contagious effects of mass shootings.

To show this, we first estimate the Poisson regression model considered by Pah et al. (2017) using their dataset which covers national, regional, and city-level monthly data on school shootings and unemployment spanning 1990-2013, extended with county-level observations. Consistently with Pah et al. (2017), regressing the number of monthly school shootings on unemployment[1] yields coefficient estimates that are statistically significant at each geographical level, suggesting a positive correlation between school shootings and prevailing economic insecurity.

However, there are grounds for scepticism. Pah et al. (2017) argue that the frequency of school shootings varies stepwise over time. They estimate four different regimes: 1990:1-1992:9, 1992:10-1994:6, 1994:7-2007:2, and 2007:3-2013:12. We show that unemployment becomes statistically insignificant when allowing for regime-specific intercepts to control for such slow-moving trends. Furthermore, the same conclusions hold when estimating the baseline regression separately for each sub-period or when including common time fixed effects in the sub-national regressions. Thus, one might worry that Pah et al. (2017)'s conclusions derive from spurious correlations and/or omitted variables.

We argue that contagious effects of shootings offer one possible explanation of the results above. The idea that particularly violent crimes are contagious is an old one (see e.g. Tarde, 1890). Recently, Towers et al. (2015) find evidence of contagion for mass killings and school shootings in the US. Figure B.5 illustrates the number of school shootings and the average fatalities per incident together with the timing of the three deadliest mass shootings in the sample (Luby's, the Virginia Tech, and the Sandy Hook shooting). Consistently with the contagion hypothesis, the number of school shootings rises persistently after these episodes.

To account for contagion, we therefore include controls for past mass shootings, and find that that massacres are highly significant in explaining school shootings in a 2-3 year window after their occurrence. Moreover, controlling for contagion, unemployment becomes insignificantly related to school shootings. Thus, contagion can explain both the statistical significance of unemployment reported by Pah et al. (2017) and the lack of significance of this parameter when changepoints are controlled for. Results generalize to the other economic indicators considered by Pah et al. (2017) and are robust to various definitions of mass shootings.

[1] The regression also includes a summer dummy as well as geographical fixed effects when analysing subnational data.

The persistent contagion effects are consistent with evidence that many school shooters were inspired by the Columbine and Virginia Tech massacres even several years thereafter (MotherJones, 2015). Another possible mechanism generating persistence is increased gun sales following massacres (Studdert et al. 2017, Table B.8) combined with the impact of gun ownership on firearm homicide rates (Siegel et al., 2013).

Our findings imply that the correlation between unemployment and school shootings uncovered by Pah et al. (2017) should not be given any causal interpretation. Instead, it derives from spurrious correlation and/or omitted variables. Mass shootings are shown to be better predictors of future school shootings but research still has to uncover why such shootings occur in the first place.

This remainder of this paper is organized as follows. Section 2.2 describes the data. Section 2.3 presents the metholodogy and main results while Section 2.4 presents the findings of various robustness exercises. Finally, Section 2.5 concludes.

## 2.2 Data

For the main analysis, we relate data on school shootings and unemployment rates at a monthly frequency for the sample period 1990-2013, at the US national, regional, and county levels.

Data on school shootings are obtained from Pah et al. (2017), containing 381 events from six original datasets pertaining to school violence.[2] Events are included on the basis of three criteria: (1) the shooting must involve a firearm being discharged, even if by accident; (2) it must occur on a school campus; and (3) it must involve students or school employees, either as perpetrators, bystanders or victims.

We mapped each of these shooting events to the respective counties where they took place and consider only the 213 counties that had one or more shooting events in our analysis. The county level data allows us better to evaluate the extent to which local labor market prospects are related to school shootings. Figure B.1 illustrates the county-level distribution of the school shootings. Shootings

[2] These include: The Brady Campaign; The School Associated Violent Deaths (SAVD) report from the National School Safety Center; Schultz et al.; Slate Magazine; Virginia Tech Review Panel; and Wikipedia. Data are available at https://amaral.northwestern.edu/school_gun_violence/.

occurred with higher frequency in the counties of Los Angeles, Cook, Wayne, Shelby, Washtenaw, and Harris. These counties coincide with the cities of Los Angeles, Chicago, Detroit, Memphis, Dallas, and Houston, respectively. Except Dallas, these cities belong to the city-sample considered by Pah et al. (2017).

Seasonally-adjusted unemployment rates were obtained from the Bureau of Labor Statistics (BLS). At the county level, unemployment rates were only available on a non-seasonally adjusted basis from BLS's Local Area Unemployment Statistics (www.bls.gov/lau). We seasonally adjusted the county-level data using the Census Bureau's X13 procedure.

We follow Pah et al. (2017) when defining regions by partitioning the U.S. according to geography and socioeconomic similarity. They broadly correspond to the 8 regions defined by the U.S. Bureau of Economic Analysis, with the exceptions that New England and Mid-Atlantic are merged and the non-contiguous states, Alaska and Hawaii, are dropped from the sample (since only two shooting events took place there).[3] The number of monthly shooting incidents differs substantially between regions. The Great Lakes, Pacific, Southeast, and Southwest regions have experienced a larger number of shooting events, with a noticeably increased rate in recent history. Whereas US regional average unemployment qualitatively experience the same general trend as the national level, there are distinct quantitative differences in unemployment rates between the regions.

We also relate school shootings to alternative economic indicators. Data on monthly national consumer confidence is obtained from the Organization for Economic Co-operation and Development (OECD). Data on labor force status flows are obtained from the Current Population Survey (Household Survey) conducted by the Bureau of Labor Statistics. Job finding rates are defined as net monthly flows from unemployment to employment, normalized by beginning-of-month unemployment. Similarly, separation rates are defined as net monthly flows from employment to unemployment, normalized by beginning-of-month employment.

[3]The resulting 7 regions consist of: (i) the Northeast (Connecticut, Delaware, District of Columbia, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont), (ii) Great Lakes (Illinois, Indiana, Michigan, Ohio, Wisconsin), (iii) Plains (Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota), (iv) Southeast (Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, West Virginia), (v) Southwest (Arizona, New Mexico, Oklahoma, Texas), (vi) Rocky Mountain (Colorado, Idaho, Montana, Utah, Wyoming), and (vii) Far West (California, Nevada, Oregon, Washington).

We consider five alternative definitions of mass shootings. The first four are obtained from the dataset compiled by MotherJones (2017)[4]. In our baseline, we define mass shootings as the three deadliest shootings on US territory, yielding the following 3 massacres: Virginia Tech (32 fatalities), Newtown Sandy Hook (28 fatalities), and Luby's massacre (24 fatalities). These stand out as much deadlier than the remaining mass shootings in the sample, with the next largest event having 14 fatalities (see Figure B.2). We first consider four yearly dummies following these three shootings. Second, we weight the three deadliest shootings by the number of fatalities. Third, we broaden our definition of mass shootings to the 10 deadliest shootings (these mass shootings have minimum 10 fatalities). Finally, we consider a very broad definition of mass shootings, which comprises the full sample from MotherJones' database. This database documents public mass shootings in which the motive appeared to be indiscriminate killing, satistfying the following criteria: (i) minimum four fatalities, (ii) the killings were carried out by a lone shooter, (iii) the shootings occurred in a public place, (iv) perpetrators who died or were wounded during the attack are not considered in the victim counts, and (v) includes a handful of cases known as "spree killings" in which the killings occured in more than one location in a short period of time, otherwise fitting the aforementioned criteria. In our sample period 1990-2013, we have 59 such mass shooting incidents. Our fifth and final mass shooting indicator is obtained from an alternative source to ensure robustness. In particular, we use the dataset on mass shootings compiled by Duwe (2007) and subsequently updated by the author. This dataset records 92 mass public shootings over the sample period, 50% more than MotherJones' sample.

To investigate the effect of mass shootings on US gun ownership, we use data on monthly gun background checks using the National Instant Criminal Background Check System (NICS), obtained from the FBI for the period spanning December 1998 to December 2013. The Brady Act, implemented by the FBI in 1998, mandates Federal Firearms License dealers to run background checks on their buyers using the NICS to determine whether prospective buyers are eligible to purchase firearms. As a result, background checks can be used as a reasonable proxy for gun purchasing demand.

[4]Data was obtained online from http://www.motherjones.com/politics/2012/12/mass-shootings-mother-jones-full-data

We also collected quarterly data on Canadian unemployment from the OECD for the period 1955 to 2017 and information on Canadian school shootings from Wikipedia at https://en.wikipedia.org/wiki/School_shooting.

## 2.3 Methodology and Results

### 2.3.1 The Nature of the Unemployment - School Violence Correlation

We study Pah et al. (2017)'s dataset extended with county-level observations on school shootings and unemployment, where data are monthly and the sample period is 1990-2013.

We initially estimate the Poisson regressions of Pah et al. (2017):

$$\mathbb{E}\left[S_m | u_m, m_s\right] = e^{\beta_0 + \beta_1 u_m + \beta_2 m_s} \tag{2.1}$$

where $S_m$ denotes the number of school shootings per month, $u_m$ is the unemployment rate, $m_s$ is a dummy for the summer months (June-August), and $\mathbb{E}$ is the expectations operator. We include geographical fixed effects to control for unobserved heterogeneity when analyzing subnational data at the regional and county level. The object of interest is $\beta_1$, the relationship between unemployment and the expected number of school shootings (controlling for the summer months).

Results are reported in Table B.1. Consistently with Pah et al. (2017), $\beta_1$ is statistically significant at each geographical level - at the US level (column 1), at the regional level (column 2) *and* at the county level (column 4). However, while unemployment is significant in (2.1), it accounts for very little of the variation in the number of school shootings. At the county level, for example, the $R^2$ is 0.0742 for (2.1) when including unemployment and 0.0706 when we eliminate it (that is, including only fixed effects and the summer dummy).

Moreover, there are further grounds for scepticism. Pah et al. (2017) argue that the arrival rate of school shootings has varied over time in a step-wise manner. They estimate four different regimes for the school shooting arrival rate, 1990:1-1992:9, 1992:10-1994:6, 1994:7-2007:2 and 2007:3-2013:12. Given this, we re-estimate equation (2.1) for each of these sub-periods and for each geographical level. The results are reported in Table B.3. Unemployment is insignificantly different from zero within *all* of these different regime-geographical level combinations at any conventional confidence. Moreover, the point estimates of $\beta_1$ are actually negative for around half of the sub-samples.

One might worry that the insignificance of unemployment derives from lack of within-regime variation in unemployment. This, however, is not the case. The standard deviation of unemployment within each of the four sub-periods chronologically corresponds to 0.84, 0.36, 0.66, and 1.75, whereas the standard deviation across the four sub-period means is 1.12, suggesting that the variance of unemployment is absorbed only in-part by the sub-period dummies.

The insignificance of unemployment is confirmed if we alternatively estimate:

$$\mathbb{E}\left[S_m|u_m, m_s, r_j\right] = e^{\beta_0+\beta_1 u_m+\beta_2 m_s+\beta_{3,j} r_j} \tag{2.2}$$

where $r_j$, $j = 1, 2, 3$, is a dummy variable that controls for the regimes with $j = 1$ indicating the 1992:10-1994:6 sub-sample, $j = 2$ indicating 1994:7-2007:2 and $j = 3$ indicating the last regime, 2007:3-2013:12. The results are reported in Table B.2. We find that $\beta_{3,1}$, $\beta_{3,2}$, and $\beta_{3,3}$ are significantly positive at each geographical level but $\beta_1$ is again insignificantly different from zero at every geographical level.

The $r_j$ dummy can be thought of as a limited control for common time effects. The insignificance of unemployment is further confirmed by explicitly including time dummies in regional and county-level estimations of equation (2.1). In Table B.1 columns 3 and 5, we report the estimates of $\beta_1$ allowing for both location and common time fixed effects and in both cases unemployment is insignificant at any conventional confidence level.

In summary, estimating equation (2.1) confirms Pah et al. (2017)'s regression results and we find that unemployment is also statistically significant even at the county level; this statistical significance, however, disappears once we control for the different regimes, showing that the unemployment link to school shootings is at best a longer-term relationship.

To test this further, we decompose the unemployment and school shootings series using the Hodrick-Prescott filter (with smoothing parameter 129,600 commonly used for monthly data) into a business cycle component (capturing variability at business cycle frequencies of approximately 1.5 to 8 years) and a trend component (capturing lower frequency movements in the time series). In Figure B.3, we show that the correlation between unemployment and school shootings is almost zero at business cycle frequencies and is instead driven by longer-term trends.

The fact that the correlation structure derives mostly from low frequency fluctuations might indicate spurious correlation issues due to near random-walk behavior. To check this formally, we re-estimated (1) at the national level, replacing unemployment with simulated random walks for a sample period matching Pah et al. (2017). Repeating this procedure 10,000 times, we generated the cumulative distribution function of the t-statistic for the random walk (see Figure B.4). The absolute value of the t-statistic exceeds the value 1.64 (1.96) in 62% (54%) of the cases. This does seem to indicate that spurious correlation may be an issue.

### 2.3.2 Contagion: A Possible Explanation

We now argue that contagion may explain both the statistical significance of $\beta_1$ reported by Pah et al. (2017) and the lack of significance of this parameter when change-points for the rate of school shootings are controlled for.

Table B.4 reports least squares estimates from the regressions:

$$S_{i,m} = \alpha + \lambda_i^{US} S_{US,m-1} + \alpha_i + \epsilon_{i,m} \tag{2.3}$$

where $i =$US (aggregate US), RE (regional) or CO (county) indicates the geographical level of the data and $m$ indicates the date. The estimated coefficient $\lambda_i^{US}$ is positive and significant at all geographical levels implying that the expected number of school shootings at the national, regional and county levels increase when past US-level shootings were high.[5] This evidence of persistence of school shootings contradicts the independent arrival rate assumption of the Poisson model.

However, this contagion does not occur at the county level. Table B.5 reports the estimates of $\lambda_i^{CO}$ when we replace US shootings $S_{US,m-1}$ with local level shootings $S_{i,m-1}$ as a regressor in equation (2.3)). The estimate of $\lambda_{CO}^{CO}$ is insignificantly different from zero implying that there is no evidence that an increase in the number of school shootings in a given county increases the expected number of school shootings in that same county.[6]

[5] $\lambda_i^{US}$ remains statistically significant if one also controls for lagged unemployment in equation (2.3).

[6] This is consistent with Towers et al (2015) findings that “the time between incidents was not significantly correlated to the distance between them" and “the Mantel test for temporal/geospatial clustering in the samples did not return significant p-values". Towers et al (2015) state that

This impact of past national school shootings may plausibly derive from contagious effects of mass shootings. Figure B.5 illustrates the time paths of the number of school shootings and the average fatalities per incidence together with the timing of the three largest massacres in the sample period: Luby's shooting (1991), the Virginia Tech shooting (2007), and the Sandy Hook shooting (2012). Luby's shooting in occurred October 1991 when George Hennard shot dead 23 people and wounded 27 others in a restaurant in Texas; the Virginia Tech shooting took place in April 2007 when Seung-Hui Cho shot dead 32 people and wounded 17 others in two separate shootings at the Virginia Polytechnic Institute and State University in Blacksburg, Virginia; and the Sandy Hook shooting was in December 2012 when Adam Lanza shot dead his mother as well as 26 kids and staff members at the Sandy Hook Elementary School in Newtown, Connecticut.

It is evident that the number of school shootings rises persistently after each of these episodes. To explore this formally, we extend equation (2.1) to include dummy variables for the periods following each of these massacres:

$$\mathbb{E}\left[S_m | u_m, m_s\right] = e^{\beta_0+\beta_1 u_m+\beta_2 m_s+\beta_{3,i} d_i} \tag{2.4}$$

where $d_i$, $i = 1, 2, 3, 4$ is a dummy variable that takes the value of 1 for the first, second, third, and fourth years following each of the three massacres. Results are presented in Table B.2. We find that $d_1$, $d_2$, and $d_3$ are statistically significant at all geographical levels (and $d_4$ is significant at the regional level) indicating support of the contagion hypothesis. Moreover, $\beta_1$ is insignificantly different from zero once such contagion is accounted for. One possible interpretation of this result is that the different regimes estimated by Pah et al. (2017) are related to the mass shootings.

We also estimate a specification where $d_i$, $i = 1, 2, 3$ is a dummy variable that takes the value of 1 for three years after Luby's shooting, the Virginia Tech shooting, and the Sandy Hook shooting, respectively (see Table B.6 ). Again the mass shootings are significant predictors of the number of school shootings and $\beta_1$ is insignificantly different from zero once such contagion is controlled for.

To ensure that our results are not driven by our selection of mass shootings, we consider alternative definitions. First, we weight the mass shootings by the

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"this lack of temporal/geo-spatial correlation is consistent with what would be expected if the contagion process is potentially due, for instance, to widespread media attention given to mass killings and school shootings".

number of fatalities. Second, we broaden our definition of mass shootings to the 10 deadliest shootings (these mass shootings have minimum 10 fatalities). Finally, we consider a very broad definition of mass shootings, which comprises the full sample from MotherJones (2017) database. In our sample period 1990-2013, we have 59 such mass shooting incidents.

When we control for contagion from these mass shooting incidents, we find that unemployment is not significant in explaining school shootings. This result is robust to all definitions of mass shootings, from the narrowest which considers only the three deadliest incidents, to the broadest which considers all incidents with minimum four shootings satisfying the public mass shootings criteria defined by Mother Jones (see Table B.7). Similarly, the results hold using Duwe's data on mass shootings (see Table B.2).[7]

The very persistent contagion effects of mass shootings that we estimate (up to 3 years) are consistent with evidence that many school shooters were inspired by the Columbine and Virginia Tech massacres even after several years, see MotherJones (2015). An additional potential mechanism generating persistent effects is that shootings increase gun sales, see Studdert et al. (2017). In line with this, in Table B.8 we show that the annualized growth rate of background checks needed for purchasing a gun rises significantly for several months after the mass shootings. This translates into a large permenent rise in the level of gun ownership (note, however, that the level eventually stabilizes since the growth rate turns negative at a 12-month horizon). Moreover, Siegel et al. (2013) show that gun ownership is robustly correlated with firearm homicide rates.

One potential worry with these results is that unemployment may have predictive power for mass shootings. In Table B.9 we report the results of the Poisson regression where we relate the incidence of mass shootings to unemployment (and a summer constant). We find the coefficient on unemployment in this Poisson regression to be insignificant. This result is robust to the source of the data for mass shootings (column 1 reports results for our main data source while column 2 reports results using Duwe's database).

[7] The two datasets identify the same shooting events as the three and ten deadliest incidents, therefore we report results only for all mass shootings when considering the Duwe data.

## 2.4 Robustness Exercises

### 2.4.1 Alternative Economic Indicators

In addition to unemployment rates, Pah et al. (2017) estimate how the number of school shootings is affected by consumer confidence. Here we show that the results reported above hold true when considering the link between school shootings and consumer confidence rather than the school shootings - unemployment relationship. Moreover, much of their discussion is centered around the impact of the school-to-work transition on school violence. Therefore, we also investigate how job finding rates and job separation rates correlate with school shootings.

Table B.10 reports the results of re-estimating equation (2.1) substituting unemployment with consumer confidence, job finding rates or job separation rates, respectively. $\beta_1$ has the predicted sign and is statistically significant for all three indicators: economic security (higher consumer confidence, higher job finding rates, and lower separation rates) is associated with reduced shootings, consistent with the arguments of Pah et al. (2017).

In Table B.12 we report the results of estimating equation (2.4) when using each of these three alternative indicators as regressors instead of unemployment. As above, the estimates of $\beta_1$ become insignificantly different from zero once we control for periods following the three largest shooting massacres. Statistical insignificance is also robust to including sub-period dummies and dummies for the three massacres (see Tables B.11 and B.13). Since these indicators are highly correlated with unemployment, they are subject to a similar spurious correlation.

### 2.4.2 Robustness to Specification Choice

One might worry that our conclusions are sensitive to sampling errors and that they would change if we compute standard errors that are robust to heteroscedasticity or cluster them by states. To check this, Table B.14 repeats Table B.1 using robust standard errors or clustering by state. All conclusions remain unchanged. In Table B.15 we extend the results reported in Table B.3 to the case of robust standard errors. Again, no conclusions change. Table B.16 contains the results of estimating equation (2.2) using robust standard errors; all conclusions remain robust. Table B.17 contains the results when estimating (2.4) with robust standard errors or with state clustering and again conclusions reported earlier continue to hold true. Finally, Table B.18 is the equivalent of Table B.6 using robust standard errors or clustering and again conclusions are unaltered.

Another issue concerns the fact that the Poisson model tends to underestimate the number of observations without shootings. One way of addressing this is to model shootings using a Zero Inflated Poisson (ZIP) model. This essentially allows zero observations to derive either from the Poisson process itself or from another binary process. In Table B.19 we report the estimates of equation (2.1) using the ZIP model where we specify the inflated model as a logit. We also report the Vuong test which tests the ZIP model against the standard Poisson model. The ZIP model is preferred to the standard Poisson model only at the 10 percent level for the national and regional data indicating that the earlier results in Table B.1 are appropriate.[8] Finally, Table B.20 applies the ZIP model to (2.2). Again, the standard Poisson model is preferred for the national data. For regional data instead, the test statistic prefers the ZIP model. In the latter case, there is mild evidence from the logit model that unemployment matters for whether shootings occur or not (but not for how many). The parameter is, however, only significant at the 10 percent level.

Thus, we conclude that the results are robust.

### 2.4.3 Evidence for Canada

In principle, it would be very interesting to repeat Pah et al. (2017)'s analysis for other countries to examine cross-country evidence. Luckily, the U.S. stands out as special due to the high incidence of school shootings; such events are rare in most developed economies. Nonetheless, we repeated Pah et al. (2017)'s analysis for Canadian data. Since 1955 there have been 15 school shootings in Canada, and 12 out of these span the period 1976-2015. Allowing for quarterly time dummies, the estimate of $\beta_1$ in equation (2.1) is statistically insignificantly different from zero at any conventional confidence level (see Table B.21). Figure B.6 illustrates the time paths of unemployment and school shootings in Canada.

[8] We do not report ZIP estimates for county level data because the likelihood was not well-behaved when allowing for county level fixed effects.

## 2.5 Conclusion

Few things may matter as much to US parents as their off-springs' health and safety. For that reason, the results of Pah et al. (2017) and their interpretation are very important. We argue that the correlation between unemployment and school shootings cannot be given causal interpretation. Mass shootings are better predictors of future school shootings but research has to uncover why such shootings occur in the first place. Providing sound evidence on this will obviously be of first-order importance.

# Chapter 3

# Sentimental Business Cycles

*Joint with Evi Pappa and Morten Ravn*

## 3.1 Introduction

A central topic in macroeconomics concerns the sources of fluctuations in the economy and their propagation mechanisms. An extensive literature has seeked to provide empirical evidence on the impact of 'identified' shocks (e.g. see the recent comprehensive survey of Ramey, 2016). This literature has focused upon estimating 'fundamental shocks' such as monetary and fiscal policy shocks, technology and investment-specific shocks, oil price shocks, credit shocks, uncertainty shocks, or shocks to labor supply. However, under a variety of conditions, the economy may also fluctuate over time in response to non-fundamental shocks, such as expectational errors or "animal spirits". There is however, very little *direct* evidence on the impact of such shocks and how they propagate over time. This paper addresses this issue. We estimate the impact of autonomous changes in consumer sentiments and relate the results to economic theory. We show that a worsening in consumer sentiments has persistent recessionary effects on the economy.

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

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

In order to examine this, we draw on a database of mass shootings constructed by MotherJones (2017), recording incidents with minimum four fatalities (excluding the perpetrator) carried out by a lone shooter in a public sphere. The MotherJones database covers August 1982 to June 2017 and we extend this data back to 1960. In this sample, there were no less than 754 fatalities deriving from 98 separate events with the most lethal ones being the 2016 Orlando nightclub massacre (49 fatalities) and the Virginia Tech massacre in April 2007 (32 fatalities).

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

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

Augmenting the VAR with additional data series (one at a time) sheds light on dynamic responses for a myriad of macroeconomic variables. Shocks to consumer sentiments are shown to reduce consumption of both durables and nondurables and increase private saving rates. Moreover, the rise in savings is biased towards safer assets, consistent with a story of precautionary savings. Firms reduce the use of factor inputs, shown by a reduction in capacity utilization and hours worked. Labor market tightness falls both due to a rise in unemployment and a fall in vacancies posted by firms. On the other hand, the negative shock to confidence is inflationary and associated with significant increases in asset prices as well. Most importantly, a deterioration of consumer sentiments is robustly accompanied by a significant drop in the nominal interest rate. Given the rise in consumer basket and asset prices, monetary policy seems to react directly to the sentiment shock. Indeed, we show that the measures of monetary policy shocks proposed by Romer and Romer (2004) and Gertler and Karadi (2015) react significantly to our identified sentiment shocks.

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

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

In this framework, a negative technology shock leads to a persistent fall in output and its components, and a persistent rise in unemployment and inflation. On the other hand, a deterioration in sentiments leads to a temporary fall in output, consumption, and the job finding rate, and a more persistent increase in unemployment coupled with a temporary increase in inflation. These effects accord well with our empirical findings but contrast most of the predictions of existing models on the effects of noise shocks (see, e.g., Lorenzoni, 2009) that usually characterize sentiment shocks as demand shocks that move output and inflation in the same direction.

The mechanism behind these dynamics is based, as in the existing models, on the consumers' Euler equation. Forward-looking consumers expect their future incomes to be driven by the persistent technology shock. A negative sentiment shock temporarily decreases their expectation of future productivity, and should, in principle, reduce future expected consumption. Differently from the existing models, in the presence of search and matching frictions, what is crucial is the expectations agents form about their job finding rate and how this relates to their future consumption. An expected decline in the job finding rate increases the risk of becoming unemployed and hence makes employed households want to save more for precautionary motives and decreases demand. Yet, this mechanism does not involve all households. Under incomplete markets, only employed households lose from an expected fall in wages and the demand channel highlighted in the existing literature is weakened. As a result, as long as wages are sufficiently flexible and as long as the real productivity shock is not very persistent, the non-fundamental shock can induce, as we see in the data, a fall in output and at the same time inflationary pressures, even when the real interest rate falls on impact after the shock.

Our work is related to recent empirical studies that have tried to identify the macroeconomic effects of sentiment shocks. Mian et al. (2015) use two recent episodes in US presidential elections that led to the loss of the incumbent president and identify sentiment shocks as pessimism regarding government policy, resulting when a high share of the county electorate supported the incumbent president and (s)he lost the elections. They conclude that government policy sentiment shocks have limited effects on households' spending. In a similar vein, Benhabib and Spiegel (2016), using cross-sectional information in state data, examine the relationship between state GDP growth and sentiment. Posing that agents in states with a higher share of congressmen from the political party of the sitting president are more optimistic, they show that improvements in sentiment are associated with persistent and sizeable increases in economic activity. Similar conclusions are also drawn in the work of Lagerborg (2017) that uses school shootings as an instrument to identify sentiment shocks at the local level.

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

The rest of the paper is organized as follows: the next section describes the data and the empirical framework. Section 3.3 presents our empirical results while Section 3.4 presents the theoretical model. Finally, Section 3.5 concludes.

## 3.2 Data

### 3.2.1 Consumer Confidence

To measure consumer confidence, we use data collected by the University of Michigan in its Survey of Consumer Confidence. This survey has been conducted since the late 1940's (initially annually, quarterly from 1952 and monthly from 1977) and the extended sample period makes it appealing for time-series analysis. We start our sample in 1960 and linearly interpolate the consumer confidence data prior to 1977 to produce a monthly series. Each month approximately 500 randomly selected persons are surveyed by phone and are asked a variety of questions relating to their personal finances and to the aggregate U.S. economy.[1] Answers are aggregated across respondents and across questions to produce various U.S. consumer confidence indicators. Three broad indices are computed: the Index of Consumer Sentiment (ICS), the Index of Current Economic Conditions (ICC) and the Index of Consumer Expectations (ICE). The first of these is a broad index covering respondents' views about both current and expected future conditions of their own finances and of the U.S. economy, while the ICS focuses on

[1] A subset of the respondents are surveyed twice, with a six-month time interval in between, but the majority of subjects are new. Hence, some of the time-variation in the indicies is due to rotation of the survey subjects.

the current situation and the ICE is based upon the forward-looking questions. We focus on the ICE as the measure of confidence in our analysis because of its forward-looking nature.

The ICE is calculated using responses to three questions: (i) "Now looking ahead–do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?"; (ii) "Now turning to business conditions in the country as a whole–do you think that during the next twelve months we'll have good times financially, or bad times, or what?"; and (iii) "Looking ahead, which would you say is more likely–that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?" For each question, which are commonly referred to as PEXP, BUS12, and BUS5, respectively, the survey subjects are given the choice of a positive, neutral or negative answer. The index is then computed by subtracting the percentage of negative respondents from the percentage of positive respondents plus 100, and the scores are normalized relative to the 1966 base period.

### 3.2.2 Other Variables in the VAR

In addition to log consumer confidence, the other variables in the baseline VAR consist of: the civilian unemployment rate, log industrial production, annual consumer price index (CPI) inflation, and the federal funds rate. Data is monthly spanning January 1960 to June 2017 and was retrieved from the Federal Reserve Bank of St. Louis (FRED). Data for the unemployment rate and consumer price index for all urban consumers are produced by the Bureau of Labor Statistics. Data for industrial production index and the effective federal funds rate are produced by the Board of Governors of the Federal Reserve System.

Figures C.1 and C.2 plot log ICE alongside log industrial production and the unemployment rate, respectively, where all data are detrended with a fourth-order time polynomial. Consumer confidence tends to peak at the late stages of expansionary phases and reach its troughs just prior to economic recoveries. There are exceptions to this, though, including faltering consumer confidence as the U.S. partially recovered from the Great Recession in late 2009 - early 2010. The overall contemporaneous correlation between ICE and detrended industrial production is 32 percent. Unemployment and consumer confidence typically move oppositely but there are, again, exceptions such as the late 1970's - early 1980's where the two series appear to comove positively. Nevertheless, there is a somewhat stronger relationship between unemployment and consumer confidence than between consumer confidence and industrial production with a contemporaneous correlation of -47 percent.

We also augment the baseline VAR with additional variables. Data on real durable and nondurable goods' personal consumption expenditures is obtained from the U.S. Bureau of Economic Analysis. Data on capacity utilization, which refers to percent of capacity being employed in the manufacturing sector, is produced by the Board of Governors of the Federal Reserve System starting in 1967. We obtain data on labor utilization, measured as the average weekly hours per worker for which pay was received of production and nonsupervisory employees in the manufacturing sector, from U.S. Bureau of Labor Statistics. Data on vacancies is taken to be help-wanted advertising in newspapers (produced by the National Bureau of Economic Research) whereas labor market tightness is constructed as the ratio of vacancies to the total number of unemployed (compiled by the U.S. Bureau of Labor Statistics).

We also consider a series of variables associated with savings and a rush safe assets. We obtain data on personal saving rates, calculated as the ratio of personal savings (personal income less personal outlays and personal taxes) to disposable personal income, produced by the U.S. Bureau of Economic Analysis. Long-term government bond yields, measured as the 10-Year Treasury constant maturity rate (measured in percent) is produced by the Board of Governors of the Federal Reserve System. Data on Moody's seasoned AAA and BAA corporate bond yields (measured in percent), based on bonds with maturities 20 years and above, are used to construct measures of spreads that relate to asset safety. Data on real gold prices, measured in US dollars per troy ounce, is obtained from the ICE Benchmark Administration Limited and deflated by CPI. Bureau of Labor Statsitics.

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

All variables except for interest rates (federal funds rate, government bond yields, and AAA and BAA spreads) are seasonally adjusted. All data except for these interest rates, and other variables defined as ratios (e.g. labor market tightness and saving rates) are expressed in natural logarithms.

### 3.2.3 Mass Shootings

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

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

The two sources of data on mass shootings agree on the most serious incidents which we record in Table C.1. 15 incidents resulted in 10 or more fatalities.

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

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

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

### 3.2.4 Estimation

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

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

$$\mathbf{A}\left(\mathbf{L}\right)\mathbf{Y}_t = \mathbf{u}_t \tag{3.1}$$

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:

$$\mathbf{u}_t = \mathbf{\Theta}_0\mathbf{e}_t \tag{3.2}$$

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

$$\mathbf{Y}_t = \Gamma\left(\mathbf{L}\right)\mathbf{\Theta}_0\mathbf{e}_t \tag{3.3}$$

where $\Gamma\left(\mathbf{L}\right)$ is square summable. The identification problem amounts to identifying $\mathbf{\Theta}_0$. In our application we are interested in identifying only a single shock, say $\mathbf{e}_{1t}$, and therefore wish to identify only one column of $\mathbf{\Theta}_0$. Let consumer confidence be the first element of the vector of observables, $\mathbf{Y}_t$, and assume that fatalities of mass shootings, $\mathbf{s}_t$, satisfies the following identifying assumptions:

$$\begin{array}{lcc} \mathbb{E}\left(\mathbf{s}_t\mathbf{e}_{1t}\right) = \phi \neq 0 & & (\quad \text{relevance} \quad) \\ \mathbb{E}\left(\mathbf{s}_t\mathbf{e}_{it}\right) = 0 \quad , & i > 1 & (\quad \text{exogeneity} \quad) \end{array} \tag{3.4}$$

The relevance condition in (3.4) says that the proxy is correlated with the structural shock of interest while the exogeneity condition requires the proxy to be orthogonal to other structural shocks. Imposing the identifying assumptions implies that:

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

Subject to these identifying assumptions, the dynamic causal effects of consumer sentiment shocks are identified up to a scale factor. We scale the structural impulse responses so that the sentiment shock corresponds to a one percent decline in the consumer confidence index, i.e. $\mathbf{\Theta}_{0,11} = 1$. The other structural coefficients of interest can then be obtained as:

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

With strong instruments, these coefficients can be estimated by IV regressions of the innovations $\mathbf{u}_t$, $\widehat{\mathbf{u}}_t$, on $\widehat{\mathbf{u}}_{1,t}$ using $\mathbf{s}_t$ as the instrument. The impulse responses then follow from (3.3) using the sample estimate of the structural sentiment shock, $\mathbf{e}_{1,t} = \varphi' \mathbf{u}_t$.

## 3.3 Empirical Results

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

### 3.3.1 Mass Shooting Fatalities as an Instrument

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

An existing literature argues that terrorist attacks have an impact on psychological well-being, including confidence. A field experiment of Lerner et al. (2003), in the aftermath of the 9/11 attacks on the Twin Towers, suggests that individuals react to such events with very pessimistic views about their own – and the average American's – exposure to risk, which would indicate some decline in confidence measures. Moreover, policy institutions such as the OECD have highlighted consumer confidence as one of the transmission channels through which terrorist attacks impact the economy (e.g. Lenain et al., 2002) and studies such as Abadie and Gardeazabal (2003) have shown that terrorism induces significant economic costs. However, while terrorist attacks may satisfy the relevance assumption, the exclusion restriction is arguably less credible. In particular, terrorism involves an inherently political form of violence and might induce public fear for further attacks. This could possibly raise economic costs in terms of spending on policing and national security. Mass shootings tend not to be connected to a group nor general cause and, as a result, cannot be interpreted as an act of terrorism. Indeed, while Baker et al. (2016) find that terrorist attacks such as 9/11 prompt spikes in uncertainty, when we use mass fatalities to instrument measures of uncertainty such as the VIX, the F-statistic is close to zero (0.02). Thus, we argue that mass shootings are an appropriate instrument to identify surprise changes in confidence that are orthogonal to second-order moment (uncertainty) shocks.

Impacts on psychological well-being have also been documented for mass shootings. Hughes et al. (2011) evaluate the impact of the Virginia Tech shooting in 2007 on PTSD symptoms amongst Virginia Tech students in the months after the tragic event. They find that PTSD symptoms were elevated for an extended period even amongst students who were not under direct threat during the shooting. Clark and Stancanelli (2017) document a decline in subjective well-being and an increased feeling of meaningfulness across the U.S. in the aftermaths of the 2012 Sandy Hook School shooting and of the 2013 Boston Marathon Bombing. Moreover, according to Fox and DeLateur (2013), although mass shootings take the fewest lives of any other type of homicide, these events induce the most fear in people due to the seemingly random nature of the events and inability to predict and prevent incidents.

An important transmission mechanism through which information about such events are transmitted to a large proportion of the U.S. population is the news coverage of these tragic events. For example, according to Lexis Nexis, a provider of electronic access to legal and journalistic documents, 182 articles have been written on the Fort Hood Massacre in Texas in 2009 (which incurred in 13 fatalities) and 156 articles on the Newtown school shooting in Connecticut in 2012 (which incurred in 28 fatalities) covering the shootings in main *national* news sources in the US.[2] Lankford (2018) studies news coverage of the perpetrators of seven mass killings in the 2013-17 period (including the Orlando nightclub shooter and the

[2] 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).

perpetrator of the San Bernadino mass shooting) and finds that mass killers received considerable news attention, in many cases more than celebrities such as sports stars. Towers et al. (2015) find that mass killings are contagious in the US through media coverage. Along the same lines, Pappa et al. (2018) show that mass shootings are good predictors of future school shootings, consistent with the existence of contagion effects.

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

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

Finally, mass shootings are largely unpredictable events and are therefore likely to satisfy the exogeneity restriction.[3] First, they are essentially uncorrelated with the aggregate U.S. unemployment rate (correlation coefficient -0.0003). Moreover, we estimate a Poisson regression for the number of mass shooting events and a Probit regression for a mass shooting dummy (equal to one if at least one mass shooting occurred) to check whether the events can be predicted.

[3] In earlier work, Pappa et al. (2018) we show that this is also true for school shootings.

Both specifications indicate that the unemployment rate is insignificant (see Table C.3). As such, no compelling evidence suggests these events are triggered by prevailing conditions in the economy. In line with this, more than 60% of perpetrators have been diagnosed with signs of mental illness even prior to committing the mass shootings according to MotherJones (2017), suggesting that the they are deeply disturbed individuals with long-term issues. Moreover, mass shootings occur with a sufficiently high frequency in the U.S. that it is unlikely that each individual event induces significant direct economic costs, giving additional credibility to the exclusion restriction.

### 3.3.2 Impulse Responses

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

**Benchmark Results**

Figure C.4 shows the identified impulse responses of the benchmark VAR to the consumer sentiment shock. The central empirical result is that an autonomous decline in consumer sentiments sets off a persistent deterioration in the economy. Industrial production is roughly unaffected on impact but then starts decreasing persistently reaching its largest decline around a year after the deterioration in consumer sentiments. Thereafter, industrial production starts recovering, but very gradually. At the 95 percent level, the drop in output is significant for 16 months (from 4 to 20 months after the shock).

We also find a significant impact of consumer sentiments on the unemployment rate. Following the decline in consumer confidence, unemployment rises on impact and keeps rising for several months, reaching the maximum increase 18 months after the decline in sentiments, slightly later than the peak in output. Thereafter, unemployment starts to recover but at a slow rate so that unemployment still is significantly above zero for a further 10 months (at the 95 percent level).

On the monetary side, we find that the negative consumer sentiment shock leads to a very persistent rise in inflation. The initial rise in inflation is robust across specifications, while the longer-term effects on the price level are more sensitive to the VAR specification. At the same time, the short-term nominal interest rate declines on impact and remains below its initial level for more than 2 years. Given the increase in inflation, the interest rate response appears to indicate that the monetary authority directly responds to consumer sentiment shocks, rather than simply responding indirectly due to the impact of sentiments on the economy. To investigate this in more detail, Figure C.5 illustrates the impulse response of the cummulated series of monetary policy shocks identified by Gertler and Karadi (2015) using local projection methods. We find that our identified sentiment shocks can predict this series, leading to a long-lasting monetary policy expansion. Finally, we also regress the Romer and Romer (2004) shock series on our identified sentiment shock and find they exhibit significant correlation (with coefficient estimate 0.03 and p-value 0.02).

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

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

We also show that a drop in consumer sentiments prompts an increase in savings and demand for assets. Figure C.9 illustrates how that the documented decline in consumption is accompanied by a sharp rise in the private savings rate upon impact of the consumer sentiment shock. The increase in savings is significant for approximately 20 months, considering a 95 percent confidence interval. This shift from consumption to savings is mirrored in rising asset prices, such as real gold and stock prices (see Figure C.12). While gold is commonly believed to be a "safe haven" in times of financial uncertainty (since it is not at risk of becoming worthless, unlike fiat currencies or other assets bearing credit risk), stocks are usually considered to be risky assets. The real rise in stock prices, albeit smaller and shorter-lived, can therefore be taken as evidence reflecting an increase in demand for savings in general. Higher savings appetites would also increase the demand for treasuries, consistant with the drop in interest rates observed for the 1-year and 10-year constant maturity Treasury bills (see Figure C.10).[4] Figure C.11 illustrates that yields on riskier bonds rise relative to safer bonds to compensate investors for higher risk, as demand rises relatively more for safer assets. The spread of AAA corporate bonds over 10-year treasury bonds is shown to rise whereas the spread between safer AAA bonds and riskier BAA ones falls. All in all, these results support the hypothesis that negative confidence shocks induce a rush to safe assets, emblematic of a "precautionary" savings motive.

An important check on our results is the extent to which the identified consumer sentiment shock may be confounded with other shocks. Barsky and Sims (2012) study the impact of innovations to consumer confidence, identified using a Cholesky decomposition of the covariance matrix in a VAR framework, and argue, on the basis of a DSGE model, that the responses are consistent with consumer confidence innovations mainly reflecting news about future TFP. To verify that the confidence shock we identify does not resemble negative "news shocks" – which are known in the literature to anticipate persistant declines in TFP – we augment the vector of observables with the utilization-adjusted TFP series estimated by Fernald and Wang (2016).[5] We find that TFP is unresponsive to the identified consumer sentiment shock at all forecast horizons at both the 68 percent and the 95 percent level. In contrast, estimating a VAR for the same vector

[4]Note that the 1 year T-bill rate and the 10 year T-bond rate show similar negative responses to short-term interest rates, reflecting a possible reaction also to monetary policy.

[5]Updated data on the TFP process can be found on the Federal Fund of San Francisco Webpage: https://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/

of observables and imposing a triangular structure on the covariance matrix implies that TFP declines significantly at the 68 percent level after about 2 years (see Figure C.15). [6]

Along similar lines, we verify that the confidence shock we identify also does not resemble "uncertainty shocks", which are known in the literature to show impact jumps in uncertainty measures. As previously mentioned, mass shootings are highly insignificant as an instrument for uncertainty, yielding an exclusion F-test statistic that is close to zero. Nonetheless, we augment our benchmark VAR with two commonly-used measures of uncertainty: the VIX and Jurado et al. (2015)'s short-term (1-month) uncertainty index. Figure C.14 shows that uncertainty is unresponsive to the identified consumer sentiment shock on impact, and only significantly rises at the 68 percent confidence level for a few months and with a delayed response.

To sum up, in this empirical exercise we have demonstrated that fatalities resulting from mass shootings in the US are a strong instrument for consumer sentiments and, in turn, find that a deterioration in sentiments is recessionary, inflationary, and persistent. We also show a deterioration in consumer sentiments is accompanied by a monetary expansion stemming from a direct reaction of monetary policy to sentiments.

**Robustness**

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

In Figure C.18 we show the results are robust to using the measure of mass shooting fatalities derived from the Duwe (2007) dataset rather than the MotherJones (2017) data.[7]

[6] In the Online Appendix we also report results when we include the common macro uncertainty, computed by Jurado et al. (2015), the VIX and Stock Prices in our baseline VAR. The identified shocks to confidence are contemporaneously orthogonal to macroeconomic uncertainty and the stock prices react positively on impact to the confidence shock converging quickly to their pre-shock value. Notice that the shock to confidence identified through the Choleski ordering is definitely not a pure shock to confidence as it moves significantly on impact both utilization adjusted TFP and macro uncertainty measured by both the Jurado et al (2015) index and also by the VIX. Moreover, differently from our identified shock, the shock to confidence from the Choleski specification reduces significantly and persistently real stock prices.

[7] The decline in consumer confidence is slightly more persistent when using the Duwe (2007) dataset and the decrease in industrial production is slightly larger but none of these differences

One could argue that not all mass shootings affect confidence in the same way at the national level. Actually, according to Lexis Nexis, it is the mass shootings with more than 10 fatalities that enjoy a widespread coverage in the national press. We therefore present impulse responses when we instrument confidence with the shootings that had a minimum death toll of 10 persons (see Figure C.19). Results do not differ significantly from our baseline VAR, apart from the responses of industrial production and unemployment exhibiting a somewhat higher persistence. Results are also robust to weighing the mass shootings by their media coverage in main national and regional news, as reported by Lexis Nexis (see Figure C.20).

As noted in Section 3.2, the frequency – and severity – of mass shootings has changed over the sample period. In Figure C.21 we show that results are robust to detrending fatalities in mass shootings with a fourth order polynomial trend. Results are also insensitive to considering the number of mass shooting events instead of the fatalities resulting from the shootings as an instrument (see Figure C.22).

Finally, results are also found to be robust to the lag length in the VAR (as an example, Figure C.23 plots responses considering 12 lags).

## 3.4 Theory

### 3.4.1 The Model

In this section, we relate our empirical results to a theoretical model. We consider a heterogeneous agents model with matching frictions in the labor market and nominal rigidities in the goods market. The economy is subject to stochastic aggregate productivity shocks and to monetary policy shocks. Following Lorenzoni (2009), there are two components of productivity, purely transient shocks and persistent changes in productivity. Only the latter matter for expectations about next period's level of productivity. However, agents do not observe the two components separately and use a Kalman filter to form expectations about the persistent component. Agents receive signals about the persistent component

are statistically significant at conventional confidence levels. Moreover, as we report in Table C.2, the measure of fatalities in mass shootings derived from Duwe (2007) does not pass the weak instrument test for any of the different confidence indices and, as a result, we prefer not to put too much weight on the reported impulse responses.

which are composed of the its true value and a noise component that we interpret as consumer sentiments. Consistently with our empirical findings, we also allow the monetary authority, which sets the nominal interest rate, to respond directly to consumer sentiments.

**Preferences:** There is a continuum of measure one of infinitely-lived households indexed by $i$ who maximize expected discounted utility. Agents live in single-member households and face uninsurable unemployment risk. Preferences are given as:

$$\mathbf{U}_{i,t} = \widehat{\mathbb{E}}_t \sum_{s=t}^{\infty} \beta^{s-t} \left( \frac{\mathbf{c}_{it}^{1-\mu} - 1}{1-\mu} - \varsigma \mathbf{n}_{it} \right) \tag{3.5}$$

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

$$\mathbf{c}_{it} = \left( \int_j \left( \mathbf{c}_{it}^j \right)^{1-1/\gamma} dj \right)^{1/(1-1/\gamma)} \tag{3.6}$$

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

$$\mathbf{n}_{it} = \begin{cases} 0 & \text{if unemployed} \\ 1 & \text{if employed} \end{cases} \tag{3.7}$$

Employed agents earn a real wage $\mathbf{w}_t$ while unemployed agents receive an endowment $\xi > 0$.[8]

**Technology**: Output is produced using constant returns technologies:

$$\mathbf{y}_{jt} = \exp(\mathbf{A}_t) \left( \mathbf{z}_{jt} \mathbf{k}_{jt} \right)^{\tau} \mathbf{n}_{jt}^{1-\tau} \tag{3.8}$$

where $\mathbf{y}_{jt}$ is firm $j'$s output, $\mathbf{A}_t$ is an aggregate productivity shock, $\mathbf{k}_{jt}$ is the input of capital, $\mathbf{n}_{jt}$ denotes employment in firm $j$, $\mathbf{z}_{jt}$ is the capactity utilization rate, and $\tau \in [0, 1)$ is the elasticity of output to the input of capital.

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

Firms hire workers by posting vacancies, $\mathbf{v}_{jt}$, at the cost $\kappa \exp(\mathbf{A}_t)$ per vacancy. The law of motion of employment is given as:

$$\mathbf{n}_{jt} = (1-\omega)\,\mathbf{n}_{jt-1} + \mathbf{q}_t \mathbf{v}_{jt} \tag{3.9}$$

where $\omega > 0$ is the job separation rate, and $\mathbf{q}_t \in (0,1)$ is the vacancy filling rate.

Firms own the capital stock and the law of motion of $\mathbf{k}_{jt}$ is:

$$\mathbf{k}_{j,t+1} = \left(1 - \delta\left(\mathbf{z}_{jt}\right)\right)\mathbf{k}_{jt} + \mathbf{i}_{jt} \tag{3.10}$$

where $\mathbf{i}_{jt}$ denotes investment in capital by firm $j$ and $\delta\left(\mathbf{z}_{jt}\right)$ is the capital depreciation rate. We assume that $\delta'\left(\mathbf{z}_{jt}\right), \delta''\left(\mathbf{z}_{jt}\right) \geq 0$.

New employment relationships are formed in a matching market. Existing matches are dissolved at the end of the period; Vacancies are posted at the beginning of the next period; Thereafter new matches are formed, and finally production and consumption take place. The aggregate matching function is given as:

$$\mathbf{m}_t = \vartheta \mathbf{u}_t^{\alpha} \mathbf{v}_t^{1-\alpha} \tag{3.11}$$

where $\mathbf{m}_t$ denotes the measure of new matches, $\vartheta > 0$ is a constant, $\mathbf{u}_t$ is the measure of unemployed workers, $\mathbf{v}_t = \int_j \mathbf{v}_{jt} dj$ is the measure of aggregate vacancies, and $\alpha \in (0,1)$ is the elasticity of matches to unemployment.

**Prices and Wages**: Firms are monopolistically competitive and set the nominal prices of their products, $\mathbf{P}_{js}$. Firms face quadratic price adjustment costs and maximize the objective function:

$$\mathbf{\Phi}_{jt} = \widehat{\mathbb{E}}_t \sum_{s=t}^{\infty} \mathbf{\Lambda}_{j,t,s} \left[ \frac{\mathbf{P}_{js}}{\mathbf{P}_s}\mathbf{y}_{js} - \mathbf{w}_s \mathbf{n}_{js} - \mathbf{i}_t - \kappa \mathbf{v}_{js} - \frac{\phi}{2}\left(\frac{\mathbf{P}_{js}}{\mathbf{P}_{js-1}} - 1\right)^2 \mathbf{y}_s \right] \tag{3.12}$$

where $\mathbf{\Lambda}_{j,t,s}$ denotes the stochastic discount factor of the (owners of the) firms, and $\mathbf{P}_s$ is the aggregate price level. $\phi \geq 0$ denotes the extent of price adjustment costs, and $\mathbf{y}_s = \int_j \mathbf{y}_{js} dj$ is aggregate output. Firms set prices subject to (3.8)-(3.9) and subject to the demand functions for their goods:

$$\mathbf{y}_{jt} = \left(\frac{\mathbf{P}_{jt}}{\mathbf{P}_t}\right)^{-\gamma} \mathbf{y}_t \tag{3.13}$$

Given the matching frictions in the labor market, new and existing employment relationships produce a match surplus. In the matching literature it is common to assume that this surplus is divided between workers and firms in a bargaining game. An alternative is to assume that wages are constant or vary systematically with labor market conditions as long as they are consistent with a non-negative match surplus. This latter modeling is convenient in an incomplete markets set-up because it circumvents the issue that wages may be wealth dependent. For that reason we assume that the real wage is given as:[9]

$$\mathbf{w}_t = \bar{w} \left( \frac{\mathbf{J}_t}{\bar{\eta}} \right)^{\chi} \tag{3.14}$$

where $\chi \geq 0$ and $\bar{w}, \bar{\eta}$ are constants. $\mathbf{J}_t = \mathbf{m}_t / \mathbf{u}_t$ denotes the job finding rate and (3.14) accordingly assumes that real wages rise when workers are harder to hire (since the vacancy filling rate, $\mathbf{q}_t = \mathbf{m}_t / \mathbf{v}_t$ is decreasing in the job finding rate).

**Asset and Budget Constraints**: There are two financial assets, nominal bonds and firm equity, in the economy. As Ravn and Sterk (2017), we adopt a limited participation set-up assuming that only a small share of the agents, which we denote by Y, face positive returns from investing in equity. The other group of agents therefore have to rely on savings in bonds only for smoothing their consumption stream. The flow budget constraint for the agents that can participate in the stock market is:

$$\mathbf{c}_{it} + \mathbf{b}_{it} + \mathbf{x}_{it} \leq \mathbf{w}_t \mathbf{n}_{it} + \xi \left(1 - \mathbf{n}_{it}\right) + \frac{\mathbf{R}_{t-1}}{\mathbf{\Pi}_t} \mathbf{b}_{it-1} + \frac{\mathbf{R}_{x,t}}{\mathbf{\Pi}_t} \mathbf{x}_{it-1} \tag{3.15}$$

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

$$\mathbf{c}_{it} + \mathbf{b}_{it} \leq \mathbf{w}_t \mathbf{n}_{it} + \xi \left(1 - \mathbf{n}_{it}\right) + \frac{\mathbf{R}_{t-1}}{\mathbf{\Pi}_t} \mathbf{b}_{it-1} \tag{3.16}$$

Here $\mathbf{b}_{it}$ denotes purchases of bonds at date $t$, $\mathbf{x}_{it}$ are equity purchases at date $t$, $\mathbf{R}_{t-1}$ denotes the nominal interest rate, $\mathbf{\Pi}_t = \mathbf{P}_t / \mathbf{P}_{t-1}$ is the gross inflation rate between periods $t-1$ and $t$, and $\mathbf{R}_{x,t}$ is the return on equity

[9] This assumption bypasses the complication that wages may be wealth dependent in an incomplete markets setting if determined by in a bargaining game.

Households face the following borrowing constraints:

$$\mathbf{b}_{it} \geq -\varkappa \mathbf{w}_t \mathbf{n}_{it} \tag{3.17}$$

$$\mathbf{x}_{it} \geq 0 \tag{3.18}$$

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

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

$$\mathbf{R}_t = \mathbf{R}_{t-1}^{\delta_R} \left( \bar{R} \left( \frac{\mathbf{\Pi}_t}{\bar{\Pi}} \right)^{\delta_\Pi} \right)^{1-\delta_R} \exp\left(\mathbf{e}_t\right) \tag{3.19}$$

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

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

$$\mathbf{A}_t = \mathbf{A}_t^p + \zeta_t^A \tag{3.20}$$

$$\mathbf{A}_t^p = \rho_A \mathbf{A}_{t-1}^p + \varepsilon_t^A \tag{3.21}$$

where $\mathbf{A}_t^p$ denotes a persistent component of productivity with persistence parameter $\rho_A \in (-1,1)$. $\varepsilon_t^A$ is the innovation to the persistent component of productivity while $\zeta_t^A$ is a transitory productivity shock. We assume that these shocks are independent, n.i.d. with means 0 and variances $\sigma_{\varepsilon,A}^2$ and $\sigma_{\zeta,A}^2$, respectively.

Agents in the economy observe $\mathbf{A}_t$ at the beginning of the period but not the transitory and persistent components separately. They do, however, receive a signal about the persistent component:

$$\mathbf{\Psi}_t^A = \mathbf{A}_t^p + \mathbf{s}_t^A \tag{3.22}$$

where $\mathbf{s}_t^A$ is assumed to be n.i.d. with mean 0 and variance $\sigma_{s,A}^2$. We think of $\mathbf{\Psi}_t^A$ as reflecting consumer confidence and $s_t^A$ as indicating sentiments.

The innovation to monetary policy is given as:

$$\mathbf{e}_t = \varphi_A \mathbf{s}_t^A + \varepsilon_t^R \tag{3.23}$$

where $\varepsilon_t^R$ is n.i.d. with mean 0 and variance $\sigma_\psi^2$ and is assumed to be orthogonal to $\zeta_t^A$ and $\varepsilon_t^A$. Agents observe $\mathbf{e}_t$ but not $\varepsilon_t^R$. When $\varphi_A = 0$, innovations to nominal interest rates reflect the monetary policy shock $\psi_t$ only, while $\varphi_A \neq 0$ implies that innovations to interest rates in general will be a mix of sentiments and pure monetary disturbances. One way of thinking about this is that sentiments impact on all agents in the economy including members of the open markets committee. Alternatively, one might assume that the central bank receives a noisy message about consumer sentiments which impacts on its interest rate decision.

Given this information structure, agents use a Kalman filter to form expectations about $\mathbf{A}_t^p$. Define $\mathbf{x}_t^o = \left(\mathbf{A}_t, \mathbf{\Psi}_t^A, \mathbf{e}_t\right)'$, as the observable signals, and note that the law of motion of $\mathbf{x}_t^o$ can be written as:

$$\mathbf{x}_t^o = C\mathbf{A}_t^p + D\xi_t \tag{3.24}$$

where $C = (1, 1, 0)'$, $\xi_t = \left(\zeta_t^A, \mathbf{s}_t^A, \varepsilon_t^R\right)$ and

$$D = \begin{pmatrix} 1 & , & 0 & , & 0 \\ 1 & , & 1 & , & 0 \\ 0 & , & \varphi_A & , & 1 \end{pmatrix}$$

Let $\mathbf{V}_\xi = D'\mathbb{E}\left(\xi'\xi\right) D$ and denote $\mathbf{A}_{t,t}^p$ as the date $t$ expectation of $\mathbf{A}_t^p$. The solution to the Kalman filter can then be expressed as:

$$\mathbf{A}_{t,t}^p = \mathbf{\Gamma}\mathbf{A}_{t-1,t-1}^p + \mathbf{K}x_t^o$$

where

$$\begin{aligned} \mathbf{\Gamma} &= \rho_A - \mathbf{KC} \\ \mathbf{K} &= \rho_A \Sigma \mathbf{C}' \left(\mathbf{C}\Sigma\mathbf{C}' + \mathbf{V}_\xi\right)^{-1} \end{aligned}$$

and $\Sigma$ is the solution of the Ricatti equation:

$$\Sigma_{r+1} = \rho_A^2 \Sigma_r + \sigma_{\varepsilon,A}^2 - \rho_A^2 \Sigma_r \mathbf{C}' \left(\mathbf{C}\Sigma_r\mathbf{C}' + \mathbf{V}_\xi\right)^{-1} C\Sigma_r'$$

which can be solved by iteration starting from an initial positive semi-definite guess for $\Sigma_0$.

**Equilibrium and Simplifying Assumptions**: Due to the limited stock market participation and the borrowing constraint, in equilibrium agents split into three groups. The first group will be asset rich households who have access to the equity market. We assume that these agents become sufficiently rich that they drop out of the labor market due to the fixed participation cost $\varsigma$ which enters (3.5).

The second group are unemployed asset poor workers. These agents expect income to increase when they find a job and therefore would like to issue debt. However, the borrowing constraint (3.17) prevents unemployed households from borrowing and they, therefore, have to consume their flow income at most. The third group will be the employed asset poor households. These households have an incentive to save for intertemporal reasons and for precautionary reasons and are, as such, therefore not constrained by (3.17). The real interest rate therefore has to satisfy their budget constraint. Since these agents face idiosyncratic risk, the real interest rate will be lower than $1/\beta$. Asset rich households who purchase equity and drop out of the labor market, in contrast, do not face any idiosyncratic risk and will invest in equity rather than in bonds. Therefore, in equilibrium, asset poor households will consume their flow labor market equilibrium while unemployed workers will consume the endowment that they receive.

Because we assume Rotemberg (1982) style nominal rigidities and since asset rich households face no idiosyncratic risk, firms set the same prices and make the same investment, capacity utilization and employment decisions. The equilibrium conditions can then be summarized by:

$$\left(\mathbf{c}_t^e\right)^{-\mu} = \widehat{\mathbb{E}}_t \beta \frac{\mathbf{R}_t}{\mathbf{\Pi}_{t+1}} \left(\left(1-\omega\left(1-\mathbf{J}_{t+1}\right)\right)\left(\mathbf{c}_{t+1}^e\right)^{-\mu} + \omega\left(1-\mathbf{J}_{t+1}\right)\left(\mathbf{c}_{t+1}^u\right)^{-\mu}\right) \tag{3.25}$$

$$\gamma \mathbf{mc}_t = \phi\left(\mathbf{\Pi}_t - 1\right)\Pi_t - \widehat{\mathbb{E}}_t \beta \left(\frac{\mathbf{c}_{t+1}^r}{\mathbf{c}_t^r}\right)^{-\mu} \frac{\mathbf{y}_{t+1}}{\mathbf{y}_t} \phi\left(\mathbf{\Pi}_{t+1}-1\right)\mathbf{\Pi}_{t+1} + \gamma - 1 \tag{3.26}$$

$$\mathbf{mc}_t = \frac{1}{\exp\left(\mathbf{A}_t\right)}\left(\frac{\mathbf{w}_t}{\left(1-\tau\right)\left(\mathbf{z}_t\mathbf{k}_t/\mathbf{n}_t\right)^{\tau}} + \frac{\kappa}{\mathbf{q}_t} - \widehat{\mathbb{E}}_t \beta \left(\frac{\mathbf{c}_{t+1}^r}{\mathbf{c}_t^r}\right)^{-\mu} \frac{\left(1-\omega\right)\kappa}{\mathbf{q}_{t+1}}\right) \tag{3.27}$$

$$1 = \beta \widehat{\mathbb{E}}_t \left(\frac{\mathbf{c}_{t+1}^r}{\mathbf{c}_t^r}\right)^{-\mu} \left[\left(1-\delta\left(\mathbf{z}_t\right)\right) + \tau \exp\left(\mathbf{A}_{t+1}\right)\mathbf{z}_{t+1}\left(\mathbf{z}_{t+1}\mathbf{k}_{t+1}\right)^{\tau-1}\mathbf{n}_{t+1}^{1-\tau}\right] \tag{3.28}$$

$$\delta'\left(\mathbf{z}_t\right) = \exp\left(\mathbf{A}_t\right)\left(\mathbf{z}_t\mathbf{k}_t\right)^{\tau-1}\mathbf{n}_t^{1-\tau} \tag{3.29}$$

in addition to (3.19), the laws of motion of the shocks, and the solution to the Kalman filtering problem discussed above. $\mathbf{n}_t$ here denotes the aggregate employment rate defined as $\mathbf{n}_t = \frac{1}{1-\Upsilon}\left(\int_j \mathbf{n}_{j,t} dj\right)$.

Equation (3.25) is the Euler equation for asset poor employed workers and $\mathbf{c}_t^e$ denotes their consumption level, $\mathbf{c}_t^u$ is the consumption level of unemployed asset poor workers, while $\mathbf{J}_t$ is the job finding rate of unemployed workers. According to this condition, employed workers have (in addition to intertemporal smoothing) a precautionary savings motive due to the idiosyncratic unemployment risk. Equation (3.26) is the optimal price setting condition for the firms where $\mathbf{mc}_t$ denotes marginal costs which are defined in equation (3.27). This latter condition involves the intertemporal marginal rate of substitution of asset rich households, $\beta\left(\frac{\mathbf{c}_{t+1}^r}{\mathbf{c}_t^r}\right)^{-\mu}$, where $\mathbf{c}_t^r$ denotes their consumption. Equation (3.28) is the condition for optimal capital accumulation and (3.29) is the first-order condition for optimal capacity utilization.

In addition, the consumption of the asset poor agents are given as $\mathbf{c}_t^e = \mathbf{w}_t$, where the wage is given in (3.14), and $\mathbf{c}_t^u = \xi$. The (per capita) consumption level of the asset rich entrepreneurs is determined as:

$$\mathbf{c}_t^r = \frac{1}{\Upsilon}\left(\exp\left(\mathbf{A}_t\right)\left(\mathbf{z}_t\mathbf{k}_t\right)^{\tau}\mathbf{n}_t^{1-\tau} - \kappa\mathbf{v}_t - \mathbf{w}_t\mathbf{n}_t - \mathbf{k}_{t+1} + \left(1-\delta\left(\mathbf{z}_t\right)\right)\mathbf{k}_t\right) + \xi$$

where $\Upsilon$ denotes the share of asset rich households. The matching function implies that:

$$\mathbf{q}_t v_t = \mathbf{J}_t\left(1 - \mathbf{n}_{t-1} + (1-\omega)\,\mathbf{n}_{t-1}\right)$$

and the law of motion of employment is given as:

$$\mathbf{n}_t = (1-\omega)\,\mathbf{n}_{t-1} + \mathbf{J}_t\left(1 - \mathbf{n}_{t-1} + \omega\mathbf{n}_{t-1}\right)$$

Finally, we note that the vacancy filling rate and the job finding rate are related as:

$$\mathbf{q}_t = \vartheta^{1/(1-\alpha)}\mathbf{J}_t^{-\alpha/(1-\alpha)}$$

We focus on the equilibrium properties of the model in the vicinity of the steady-state where inflation is on target. Furthermore, we assume that $\bar{\Pi} = 1$ so that the central bank targets price stability. We solve the model by a log-linearization and using a method of undetermined coefficients.

### 3.4.2 Model's Predictions

We solve for the local dynamics in the vicinity of the intended steady state in response to true productivity and sentiment shocks. Although our analysis focuses on the effects of sentiment shocks, to get a better grasp of the dynamics of the model, we analyze also in detail the model responses after a true TFP shock.

**The Incomplete Markets Wedge**: Consider a log-linearization of the employed workers' Euler equation:

$$-\mu \hat{\mathbf{c}}_t^e = \left(\hat{\mathbf{R}}_t - \mathbb{E}\hat{\Pi}_{t+1}\right) - \mu\beta\bar{R}\mathbb{E}_t\hat{\mathbf{c}}_{t+1}^e - \beta\bar{R}\Phi\mathbb{E}_t\hat{\mathbf{j}}_{t+1}$$

where $\Phi = \omega\eta\left(\left(\frac{\xi}{w}\right)^{-\mu} - 1\right) - \chi\omega\mu\left(1-\eta\right)$ is an incomplete markets wedge that arises due to a precautionary savings motive.

This Euler equation differs from the complete markets version because of: (i) discounting - the fact that future consumption enters with the coefficient $-\mu\beta\overline{R}$ rather than $-\mu$; and (ii) the last term on the right hand side which relates to the precautionary savings wedge. This wedge represents the endogenous earnings risk that is driven by two forces: First, the job finding rate changes over time. A drop in the job finding rate in a bust increases earnings risk. This increases savings and suppresses demand in bad times. On the other hand, a lower job finding rate implies a fall in the real wage and a lower job loss during a bust, leading to a fall in precautionary savings in busts which raises demand. If the first effect dominates, earnings risk is countercyclical (see Ravn and Sterk (2017)) and a fall in TFP can feedback to demand through the precautionary motive and result in a fall in inflation. This occurs for values of $\Phi > 0$. Conversely, for $\Phi < 0$, the wage effect dominates and the demand for precautionary savings is procyclical and actually stabilizes the economy. The price responses in this case are dominated by the supply effect of the TFP shock that tends to increase prices and inflation driven by the increase in marginal costs after a negative productivity shock. Finally, when $\Phi = 0$, there is no endogenous risk feedback.

**Sentimental Business Cycles**: We now investigate the dynamics of the model with respect to shocks in sentiments. In the models of Lorenzoni (2009) and Barsky and Sims (2012) inflation and output (and consumption) co-move together after the noise shock, giving the consumer sentiment shock the interpretation of a "demand" shock. In these models, the short run dynamics of consumption is mainly determined by changes in household expectations about longer term productivity. When a negative sentiment shock arrives, expected income drops which drives down consumption. Evidently, this is inconsistent with the empirical results that we have discussed earlier because these indicate a negative correlation between consumption and inflation conditional upon a decline in consumer sentiments.

The central difference between the model presented here and the models analyzed by Lorenzoni (2009) and Barsky and Sims (2012) is the presence of incomplete markets.[10] In addition, we also allow consumer sentiments, the noise shock, to impact directly on monetary policy, and we have introduced matching frictions in the labor market. In our framework, a negative sentiment shock temporarily decreases agents' expectation of future productivity, and induces an expected decline in the job finding rate, as the true productivity shock. The expected fall in the job finding rate increases the risk of becoming unemployed and hence makes employed households want to save more for precautionary motives and decreases demand, as in the models of Lorenzoni (2009) and Barsky and Sims (2012). From the supply side, lower expected productivity under sticky prices increases real marginal costs for firms, which has a positive impact on inflation. Hence, our model induces a powerful demand-supply interaction and it is important to understand which assumption is crucial for overturning the standard theoretical predictions.

**Model Calibration**: The model parameters are calibrated to match moments in the U.S. economy. The monetary policy reaction to sentiments parameter $\varphi_A$ is given a value 0.1. The parameter governing price adjustment takes $\phi$ is 50. The income lost when agents become unemployed is assumed to be 15%. The parameter governing the elasticity of substitution between goods $\gamma$ is set to 5. This, together with $\phi$, should imply an average contract length just under a year. The average job finding rate is set to 0.3. The risk aversion parameter $\mu$ is set to 2. The elasticity of the capital depreciation rate with respect to capital utilization is set to 0.5. The elasticity of output to labor is 0.65. The elasticity of the matching function to unemployment is calibrated to be 0.5. The elasticity of the real wage to the job finding rate $\chi$ is set to be 0.05. The persistence of technology shocks is set to be 0.9 at an annual frequency. The standard deviation of persistent technology shocks is set to 1 whereas the standard deviation of other shocks is 4.

[10]Moreover, these authors focus on permanent technology shocks while our true TFP shocks are persistent but transitory.

According to our calibration, the implied risk wedge is positive and as a result earnings risk is countercyclical. Ravn and Sterk (2017) show that the responses of the economy to a true TFP shock crucially depend on the semi-elasticity of the wage with respect to unemployment. In particular, they show that the countercyclical earnings risk is more relevant especially because for most estimates the elasticity of the wage to changes in unemployment is low. Countercyclical wage risk induces an amplification mechanism since a worsening in the labor market conditions translates to increased unemployment risk and this increases precautionary savings, which reduces aggregate demand and, in turn, reduces new hires, amplifying the initial impact of the negative TFP shock. The fall in demand, moreover, induces deflationary dynamics after a negative TFP shock. Although our model features capital accumulation and variable factor utilization, its predictions with respect to the dynamic effects of true TFP shocks do not differ substantially.

**Impulse Responses**: Figures C.24 and C.25 depict the model impulse responses to a negative shock to sentiments, when monetary policy *does not* and *does* react directly to the sentiment shock, respectively. We show that the impact effect of sentiment shocks are non-negligible and, moreover, it is the reaction of monetary policy that crucially determines the strength of the demand versus the supply channel in producing inflationary pressures after a sentiment shock. When monetary policy does not react to the sentiment shock, the precautionary savings effect dominates and demand contracts, leading to a fall in inflation after a sentiment shock. However, if monetary policy endogenously reacts to the sentiment shock, it reduces the demand channel by decreasing considerably the real rate and inflation increases after a sentiment shock, as we observe in the data.

## 3.5 Conclusion

The empirical role of consumer sentiment shocks as a driver of business cycle fluctuations remains debated in the literature, with findings hinging upon the identification assumptions used. In this paper we remain agnostic as to what sentiment shocks should look like and use an instrumental variable approach to identify exogenous movements in consumer confidence. Mass shootings in the U.S. are shown to significantly reduce consumer confidence expectations and, using these events as a natural experiment, we then show that exogenous drops in consumer confidence generate a persistent contraction in economic activity. Moreover, the economic contraction is accompanied by a rise in inflation as well as a monetary expansion, suggesting that monetary authorities react directly to sentiment shocks. In other words, for a given set of fundamentals, a drop in consumer confidence would instigate a drop in interest rates. We then show that these dynamics are consistent with an incomplete markets model with sticky prices, where consumer sentiments are modeled as noisy signals about future TFP as in Lorenzoni (2009).

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

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

# Chapter 4

# Do Stock Market Booms Anticipate Baby Booms?

## 4.1 Introduction

Fertility rates have recently shown to embody a strong cyclical component, evidenced by declining birth rates in countries severely hit by the 2008 global financial crisis (see Figure D.1). Birth rates per woman fell respectively by 11.3% in the U.S., 9.0% in Spain, and 11.8% in Greece as of 2013, since their pre-crisis peaks. Italy saw fertility rates stabilize, when they were previously rising. In fact, pre-crisis trends in fertility rates were positive in these four countries, turning negative thereafter. While fertility has traditionally been seen as primarily a trend phenomenon, this evidence of strong cyclical behavior raises scope to study fertility as a business cycle phenomenon.

The empirical part of this paper investigates the effects of current economic conditions and expectations about the future on fertility decisions in the U.S. More precisely, it asks: How does fertility respond to shocks to current unemployment and total factor productvity (TFP)? Can consumer confidence expectations about the future state of the economy predict fertility rates? And can stock prices, by reflecting expectations of future developments in the economy, predict fertility rates? This paper contributes to the empirical literature that studies the relationship between fertility and the business cycle. To the best of my knowledge, it is the first paper to look at how news, or expectations about the future, affect fertility decisions employing vector auto-regression (VAR) methods.

Structural VAR estimation based on Choleski identification of shocks suggests that fertility is procyclical, with fertility rates rising in response to current economic conditions, such as an unexpected fall in unemployment. Fertility also responds positively to expectations, for example, to shocks to confidence about the (future) state of the economy and shocks to stock prices, which carry information about future TFP. On the other hand, fertility *declines* following positive shocks to TFP, which are highly transitory with very little persistence. These findings resonate Beaudry and Portier (2006) and Barsky and Sims (2009), who find that surprise movements in TFP are largely temporary, and that TFP instead contains an important predictable permanent component, dubbed the "news shock".

A news shock that anticipates a permanent increase in productivity generates a wealth effect that can be expected to raise fertility, resulting in a procyclical relationship. By contrast, the effect of a transitory productivity shock would operate largely via intertemporal substitution, by raising the opportunity cost of having children and thereby reducing childbearing incentives and making fertility countercyclical. In the empirical analysis I distinguish between two transitory shocks with low and high persistence.[1] In fact, the productivity shock with higher persistence is found to have a more procyclical impact on fertility rates.

I complement these results with a dynamic stochastic general equilibrium (DSGE) model that incorporates fertility into a simple real business cycle (RBC) model for married couples with a joint utility function. Children provide households with direct and durable utility, but also entail two types of costs. First, children have a consumption cost that enters the household budget constraint. Second, children have a time cost for women in terms of time away from work and leisure, while by assumption, men's labor supply is inelastic. Finally, the decision to have children is irreversible, i.e. fertility is non-negative. Fertility in the model declines on impact in response to transitory TFP shocks and rises strongly in response to news shocks that anticipate persistent increases in TFP, thereby matching the empirical impulse responses.

The remainder of this paper is structured as follows. Section 4.2 discusses the related literature. Section 4.3 presents the empirical VAR analysis. Section

[1]The latter can be thought to proxy a permanent shock to TFP.

4.4 presents the DSGE model that incorporates households' fertility choice and discusses the model's dynamics. Finally, Section 4.5 concludes.

## 4.2 Related Literature

The empirical part of this paper combines two main strands of literature. The first one looks at how fertility rates are affected by current economic conditions. Early studies found fertility rates to be countercyclical. This was the famous finding by Butz and Ward (1979), with fertility falling in good times as the opportunity costs of childbearing rose in the US over 1948-1975. Ermisch (1988) found a similar result for the UK over 1950s-1985. However, more recent analyses point to procyclical patterns in fertility. For example, Adsera (2004) found a reduction in fertility due to high unemployment for 23 OECD countries spanning 1960-1997. McNown (2003) provided similar results for the post World War II US. Finally, Örsal and Goldstein (2010) find that fertility has become positively associated with economic conditions for a panel of OECD countries over 1976-2008. These studies usually employ panel or time series econometric regressions. A vast literature studies similar questions using microeconomic methods, examining labor market determinants of fertility such as unemployment, wages, and wealth.

A smaller body of empirical literature studies how fertility responds to current economic conditions, such as unemployment, using VAR methods. Mocan (1989) suggested that both female and male unemployment rates have a negative effect on fertility, and that the behavior of fertility is pro-cyclical in bivariate VAR models but turn counter-cyclical once divorce rates are included in the VAR. Huang (2003) finds that unemployment has a negative effect on conception rates in Taiwan (and a positive effect on divorce as well as marriage rates), contrasting findings by Shieh (1994). Another paper estimates savings and fertility simultaneously employing a VAR and finds that social security has a negative effect on fertility and positive effect on household saving in Germany (Cigno et al., 2001) .

The second strand of empirical literature relates to recent studies of news shocks. Beaudry and Portier (2006) show that innovations in stock prices reflect TFP growth that is anticipated by economic agents and constitute a significant force driving business cycle fluctuations in the US. Their paper sparked renewed interest in the idea of news and expectation shocks as important factors driving macroeconomic fluctuations (Barsky and Sims, 2009). I use their identification of news shocks as revealing information about future productivity and analyze its impact on fertility decisions. A related study by Abel (2003) looks at the reverse effect of baby booms on economic outcomes such as stock prices and productivity, using an overlapping generations model in which baby booms increase national savings and investment and lead to an initial rise and subsequent fall in the price of capital (measured as stock prices). This paper, in a sense, looks at the effect running in the opposite direction, asking the question whether stock price rises anticipate baby booms.

The theoretical part of this paper contributes to the literature termed New Home Economics pioneered by Becker (1960) and Mincer (1962). This literature stresses the role of female wages, representing the opportunity cost of childbearing, as a determinant of fertility. The female wage, and hence TFP, is seen to have both positive (income) and negative (substitution) effects on fertility, with opposite effects on labor force participation.[2] The majority of this labor literature focuses on partial equilibrium choice models and is therefore less suitable for relating fertility to business cycles.[3]

Fewer papers examine fertility decisions in a general equilibrium framework. Two such papers study the baby boom that followed World War II. Greenwood et al. (2005) explain the boom as generated by a decline in the direct cost of having children. Doepke et al. (2007) explain the boom and subsequent bust by focusing on the decline and then rise in (time) opportunity cost of having children. Much of this literature uses lifecycle models (where aggregation produces variants of standard neoclassical growth models) and have a role for endogenous experience. I contribute to this literature by studying the business cycle properties of these theoretical models, by building a simple DSGE model that incorporates fertility and that can be used to study responses to aggregate technology shocks.

[2]Higher TFP would also increase the male wage resulting in a higher demand for child services. Because of the dual quality-quantity dimensions of child services, rising incomes need not necessarily result in higher fertility rates.

[3]Surveys of empirical studies of the NHE model are provided by Macunovich (1996a) and Hotz, Klerman, and Willis (1997). Critical surveys and reviews of models of fertility based on economic theories of behavior have been conducted by Olsen (1994), Macunovich (1996a), Murphy (1992), and Smith (1981).

## 4.3 Evidence from VARs

### 4.3.1 Data

I use quarterly data for the U.S.[4] spanning the period 1974Q1-2012Q3 for fertility, unemployment and consumer confidence indicators in a first VAR specification, and spanning 1980Q1-2012Q3 for fertility, TFP, and stock prices in a second specification.

I define the fertility rate as quarterly 9-month lead births per female between the ages of 15 and 54[5], which accounts for the fact that conception, on average, takes place 9 months prior to child birth. I construct data on monthly births from microdata publibly provided by the U.S. Centers for Disease Control and Prevention, while data on female population is obtained from the OECD Main Economic Indicators.

The unemployment rate is obtained from the U.S. Bureau of Labor Statistics (BLS). I construct a capacity-utilization adjusted measure of TFP by assuming a Cobb-Douglas production function and using data on real GDP (U.S. Bureau of Economic Analysis), real capital stock (Oxford Economics), industry capacity utilization rates (Federal Reserve), total hours worked in the economy (BLS), and the labor share of non-farm business (BLS). The consumer confidence indices regarding expectations and the present situation are constructed by the Conference Board Consumer Surveys. The stock price index considered is the S&P 500 composite index deflated by the GDP implicit price deflator and divided by the population. Consumer confidence, total factor productivity, and the stock price index are expressed in natural logarithms.

All variables are seasonally adjusted and detrended using a linear trend. The raw data, before trend and logarithmic adjustments, are displayed in Figures D.2 and D.3.

[4]The choice of the U.S. as a case study stems from its hands-off government policy which implies limited unemployment and maternity benefits. Thus, we would expect economic conditions to affect fertility decisions more than in countries where the state offers a wide range of benefits for having children.

[5]Prefered data on females between the ages of 15 and 44 was not available.

### 4.3.2 SVAR and Impulse Responses

#### SVAR with Unemployment and Consumer Confidence

The first specification estimates a VAR model composed of fertility rates ($f_t$), unemployment ($u_t$), and consumer confidence ($cc_t$), in this order. I consider two alternative consumer confidence indicators: (i) regarding the present state of the economy ($cc_t^P$) and (ii) regarding expectations about the future ($cc_t^F$). The structural shocks are identified by means of Choleski short-run zero restrictions, which assumes that confidence can affect unemployment and fertility decisions only with a lag but not contemporaneouly, whereas unemployment shocks can contemporaneously affect confidence. I include two lags in the VAR, suggested as optimal according to the Bayesian Information Criterion.[6]

Figures D.4 and D.5 present the impulse responses for shocks to unemployment and consumer confidence, respectively. We observe that fertility falls for a period of approximately 12 quarters in response to a shock that raises unemployment, meaning that agents respond to current economic conditions with procyclical fertility. Moreover, positive shocks to consumer confidence, related to the economy's current and future state, significantly raise the fertility rate for approximately 15 quarters. Results are robust to the measure of confidence considered.[7]

Confidence indicators can anticipate macroeconomic fluctuations for two reasons: first, because they contain "news" or information about (future) economic conditions, and second, because they contain an autonomous "animal spirit" component with causal effects on the economy. In this analysis I remain agnostic as to which of these two factors prompts the dynamic responses of unemployment and fertility rates.

In an attempt to distinguish between these two, I estimate a Proxy VAR using mass shooting fatailities in the U.S. as an instrument for confidence, in the spirit of Lagerborg et al. (2018). Autonomous "animal spirit" shocks to confidence, identified using this instrumental variable approach, show no significant impact on fertility rates (see Figure D.6).[8] This suggests that most of the procyclical response

[6] Monthly data spanning 1975M1-2013M7 gives very similar results in magnitude and significance, albeit "bumpier" IRFs.

[7] Results are also robust to a reordering of the fertility variable.

[8] Note that the "bumpy" impulse response function derives from the monthly data frequency in this VAR. The VAR comprises monthly data spanning 1974m4-2016m12 for consumer confidence expectations, industrial production, unemployment rate, consumer price index, and the federal funds rate. All data except for the unemployment rate and federal funds rate is in logs. All data

of fertility derives from "news" inherent in confidence indicators, reflecting information about long-run output that is anticipated.

### SVAR with TFP and Stock Price News

This second specification employs a VAR model composed of fertility rates ($f_t$), TFP ($tfp_t$), and stock prices ($sp_t$), in this order. I analyze the effects of TFP and stock price "news" shocks on fertility rates. News shocks are identified using short-run (Choleski) restrictions, which assume that shocks to stock prices do not contemporaneously affect TFP (nor fertility rates), in the spirit of Beaudry and Portier (2006).[9]

Figure D.7 plots the impulse response functions corresponding to the TFP and stock price news shocks. In the left panel we observe that fertility actually significantly *decreases* in response to transitory TFP shocks that are unanticipated (orthogonal to stock prices). The right panel, by contrast, shows that a news shock that anticipates a future persistent rise in TFP generates a significant *increase* in fertility rates for approximately 10 quarters.[10]

These impulse responses show that while fertility is generally procyclical with respect to unemployment and news shocks about future economic conditions, it turns out to be countercyclical with respect to transitory surprises in TFP. This evidence supports the idea that stock prices and consumer confidence reflect agents' expectations about the future; this is information that agents receive and process in advance. Moreover, the persistence and anticipation of TFP shocks is shown to be key in determining the overall procyclical response of fertility.

## 4.4 Theoretical Model

This section develops an RBC model that incorporates household fertility decisions and sheds light on different channels that can contribute to fertility being procyclical.

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except the federal funds rate is detrended using a fourth-order polynomial trend. The Proxy VAR is the baseline estimated in Chapter 3 extended with monthly data on U.S. fertility rates.

[9] Beaudry and Portier (2006) find that impulse responses look qualitatively the same when using the alternative assumption of zero long-run restrictions (Blanchard and Quah, 1989) whereby only the stock price news shock can affect TFP in the long-run.

[10] Results are robust to reordering of the fertility variable.

### 4.4.1 RBC Model with Fertility

#### Couples' problem

For simplicity, it is assumes that fertile couples are infinitely lived agents which maximize their expected utility subject to their joint budget constraint. They derive utility from consumption $(c_t)$, female leisure $\left(l_t^F\right)$, and number of children $(n_t)$. Their discounted expected utility function is given by:

$$\max_{\left\{c_t, l_t^F, n_t, k_{t+1}\right\}} E_0 \sum_{t=0}^{\infty} \beta^t u\left(c_t, l_t^F, n_t\right) = \max E_0 \sum_{t=0}^{\infty} \beta^t \left\{\log\left(c_t\right) + \sigma_n \log\left(n_t\right) + \frac{\sigma_l}{\eta}\left(l_t^F\right)^\eta\right\}$$

Children require additional consumption net of any government benefits received, where $\phi_c > 0$ is a fixed cost per child in the household's budget constraint.[11] Couples' joint income from working is given by the product of the wages ($w_t^F$ and $w_t^M$) and hours worked ($h_t^F$ and $h_t^M$), respectively by the female and male. Couples also invest $(i_t)$ in capital $(k_t)$ with return $(r_t)$. Consequently, couples' joint budget constraint is given by:

$$c_t + \phi_c n_t + i_t = w_t^F h_t^F + w_t^M h_t^M + r_t k_t$$

By assumption, men supply a fixed amount of labor $\left(h_t^M = \frac{1}{3}\right)$, whereas women allocate their fixed unit time endowment between working, leisure, and time spent caring for children, where the latter is diminishing in the number of children ($\psi_l < 1$). Leisure is thus given by:

$$l_t^F = 1 - h_t^F - \phi_l n_t^{\psi_l}$$

The number of children is given by children last period plus new borns. Couples decide the number of children by chosing their fertility rate $(f_t)$, which is assumed to be continuous on $[0,1]$. Children are assumed to "depreciate" at rate $\delta_n$, capturing probabilistic ageing à la Gertler (1999), whereby children switch into adulthood with a constant probability. As they turn adult they form their own

[11] This encompasses all costs of childrearing, including items such as food, education, and health. The simplifying assumption that total childrearing costs are linear in the number of children could be relaxed to allow for decreasing costs per child due to a "cheaper by the dozen effect". For example, multiple children can share a bedroom, clothing, toys, and food can be purchased in bulk quantities. The model's results are robust to allowing for this.

household and become less costly to their parents in terms of money and time.[12] The evolution of the number of children is thus given by:

$$n_t = (1 - \delta_n)\, n_{t-1} + f_t$$

where fertility is irriversible such that $f_t > 0$, and the evolution of capital is given by:

$$k_{t+1} = (1 - \delta)\, k_t + i_t$$

I further assume that $n_0$ and $k_0$ are given, and that $n_t$ and $k_t > 0$. In this model children can be interpreted as a time-intensive and irriversible durable good from which couples derive utility.

### Firms' problem

Firms operate under perfect competition and a CES production function with imperfect subsitutability between male and female labor, which gives rise to different wages for males and females. The substitutability is determined by parameter $\theta$ for the female share of hours and elasticity of substitution given by $\frac{1}{1-\rho}$. The production function takes the following form:

$$y_t = A_t k_t^{\alpha} \left[\theta \left(h_t^F\right)^{\rho} + (1-\theta)\left(h_t^M\right)^{\rho}\right]^{\frac{1-\alpha}{\rho}}$$

Aggregate productivity $(A_t)$ is the product of two transitory components: $A_t^P$ that I call "persistent" which follows an AR(1) process, and $A_t^T$ that I call "transitory" without any persistence. $A_t^T$ and $\varepsilon_t^{AP}$ are iid white-noise shocks.

$$\ln A_t^P = \rho_A \ln A_{t-1}^P + \varepsilon_t^{AP}$$

$$A_t^T,\, \varepsilon_t^{AP} \sim N\left(0, \sigma_A^2\right)$$

Firms choose the amount of capital and female labor to employ in order to maximize profits, which are given by:

[12] This simplifying assumption also means that parents' utility from having children diminishes as they grow older, which arguably is a strong assumption.

$$\max_{k_t, h_t^F} \pi_t = A_t k_t^{\alpha} \left[\theta \left(h_t^F\right)^{\rho} + (1-\theta) \left(h^M\right)^{\rho}\right]^{\frac{1-\alpha}{\rho}} - w_t^F h_t^F - w_t^M h_t^M - r_t k_t$$

### 4.4.2 Equilibrium Conditions

Equations (4.1) – (4.11) constitute the model's equilibrium equations. The first order conditions for the household are given by:

$$\lambda_t = \frac{1}{c_t} \tag{4.1}$$

$$\sigma_l \left(l_t^F\right)^{\eta-1} = \lambda_t w_t^F \tag{4.2}$$

$$\frac{\sigma_n}{n_t} = \left(\phi_c + w_t^F \psi_l \phi_l \left(n_t\right)^{\psi_l - 1}\right) \lambda_t \tag{4.3}$$

$$\beta \lambda_{t+1} = \left(r_{t+1} + 1 - \delta\right) \lambda_t \tag{4.4}$$

The first order conditions for the firm are given by:

$$r_t = \alpha \frac{y_t}{k_t} \tag{4.5}$$

$$w_t^F = (1-\alpha)\, \theta \left(h_t^F\right)^{\rho-1} \frac{y_t}{h_t^{\rho}} \tag{4.6}$$

where:

$$y_t = A_t k_t^{\alpha} h_t^{1-\alpha} \tag{4.7}$$

$$h_t = \left[\theta \left(h_t^F\right)^{\rho} + (1-\theta) \left(h_t^M\right)^{\rho}\right]^{\frac{1}{\rho}} \tag{4.8}$$

$$1 = h_t^F + l_t^F + \phi_l \left(n_t\right)^{\psi_l} \tag{4.9}$$

$$h_t^M = \frac{1}{3} \tag{4.10}$$

$$k_{t+1} = (1-\delta)\, k_t + i_t \tag{4.11}$$

Aggregate productivity is given by:

$$A_t = \exp\left(A_t^P\right) \exp\left(A_t^T\right) \tag{4.12}$$

$$\ln A_t^P = \rho_A \ln A_{t-1}^P + \varepsilon_t^{AP} \tag{4.13}$$

$$A_t^T,\, \varepsilon_t^{AP} \sim N\left(0, \sigma_A^2\right) \tag{4.14}$$

Finally, closing the model, the resource constraint is given by:

$$y_t = c_t + \phi_c n_t + i_t \tag{4.15}$$

### 4.4.3 Calibration

The model is calibrated to match average moments in the U.S. economy and family dynamics. The parameter values are summarized in Table D.1.

The quarterly discount factor is set to 0.98, yielding an annual rate of 0.92. The capital-income ratio $\alpha$ is set to 0.3 and capital depreciates at a quarterly rate $\delta$ of 3%. The elasticity of substitution parameter between females and males in production $\rho$ is 0.65 as in Doepke et al. (2007). Firms have a relative preference for males over females given by $\theta$ at 0.43, which corresponds to a 15% gender wage gap.

The parameters relating to fertility are calibrated to match empirical facts such as costs of raising children, average fertility rates, and female time spent with kids. The parameter describing expenditures per child $\phi_c$ at 0.06 corresponds to 15% of parental net income in steady state, within the range of estimates for the cost of raising a child for US median income households by the US Department of Agriculture (estimated at 19% as of 2015). The function describing the time cost of children has curvature parameter $\psi_l$ of 0.5, such that the female time spent with each additional child is decreasing in the number of children, and a level parameter $\phi_l$ of 0.09, corresponding to an average fertility rate of 2 kids per family and 3 daily hours allocated by females to care for their children. This also implies the parameter associated with the utility of children is 0.465. Finally, the rate at which children reach adulthood is 0.025, implying an average duration of 10 years in childhood.

Parameters governing the supply of female labor / leisure are calibrated to match average hours worked. The elasticity of lesiure parameter $\eta$ is set to -3 in the baseline whereas the parameter associated to the utility of female leisure $\sigma_l$ is set at 0.35, corresponding to 5.3 daily working hours for women (66% of their male counterparts). Males, instead, are assumed to work a fixed amount corresponding to 8 hours per day, representing one-third of their time endowment $\left(h^M = \frac{1}{3}\right)$.

Finally, the persistent component of technology has persistence parameter $\rho_A$ equal to 0.9 and the standard deviation of technology shocks is set to 0.1.

### 4.4.4 Model Dynamics

The predicted impact of an aggregate productivity shock (that raises wages) on fertility is ambiguous due to its two opposing effects. First, higher wages causes the opportunity cost of having children to rise, thereby creating an incentive to decrease fertility (countercyclical substitution effect). At the same time, higher incomes raise households' ability to finance the cost of having children thereby causing fertility to rise (procyclical income effect). As the substitution and income effects work in opposite directions, the net effect remains an empirical question. Given the procyclical fertility observed empirically, the income effect appears to dominate.

#### Transitory (Surprise) vs. Persistent (Anticipated) Technology Shocks

Figures D.8 and D.9 display the theoretical impulse responses to the transitory and persistent technology shocks, respectively. A one-period transitory TFP shock leads households to substitute from leisure and children (for which the opportunity cost has risen) to more hours working. Fertility responds countercyclically with a decrease in the first period, when the intertemporal substitution effect outweighs the income effect, and then rises at future time horizons.

On the other hand, a persistent, albeit transitory, TFP shock leads to a procyclical response of fertility. The larger income or wealth effect arising from a persistent increase in TFP stirs households to optimally increase the number of children.

In other words, the income effect now dominates the intertemporal substitution effect in households' fertility decision.

The result that more persistent TFP shocks cause fertility to respond more procyclically, mirrors empirical findings in the previous section for the VAR comprising fertility, TFP, and stock prices. The stock price news shock was associated with a persistent rise in TFP and procyclical impact on fertility. The surprise shock to TFP, instead, was highly transitory and countercyclically impacted fertility. The former, according to the literature, is more likely a "news shock" that anticipates movements in productivity that materialize in the future. To the extent that confidence also contains news about current and future economic developments, that can anticipate persistent movements in TFP, the same can be said about the VAR comprising fertility, unemployment, and consumer confidence. The procyclical response of fertility suggests there is a large component of TFP that is persistent and anticipated. In fact, Schmitt-Grohé and Uribe (2009) estimate that anticipated shocks explain approximately 70% of the variance of output growth, 80% of the variance of consumption growth, and 50% of the variance of investment growth. Furthermore, the increasing procyclicality of fertility is consistent with a documented increase in the persistence of output and in the quantity or quality of news that is relevant for predicting the future, and with a rising importance of (stock price and consumer confidence) news shocks (Jaimovich and Rebelo, 2009).

These results also resonate general findings in the literature contrasting the role of temporary "surprise" versus permanent "anticipated" shocks to TFP. Empirical evidence from VARs suggest that surprise movements in TFP are largely temporary and lead to an expansion in hours (due to intertemporal substitution) and output, accounting for a non-trivial fraction of their variance particularly at higher frequencies (Sims 2011; Barsky and Sims 2009). Transitory TFP shocks mimic these responses for both hours and output. Permanent TFP shocks are, by contrast, found to be largely predictable, leading to a response of TFP that is highly autocorrelated in growth rates. Good "news shocks" of higher future TFP are expansionary, leading to an impact reduction in hours worked (due to a wealth effect provided the eventual rise in technology is sufficiently large), and a small positive impact response of output, which is in turn followed by significant growth (e.g. Sims 2011; Barsky and Sims 2009).

I augment the model to allow for "news shocks" about future productiviy. The persistent component of TFP is subject to an unanticipated shock, contemporaneous as before, but now also an anticipated "news shock" $(e_{t-4})$ that affects productivity with a 4-quarter lag:

$$\ln A_t^P = \rho_A \ln A_{t-1}^P + \varepsilon_t^{AP} + e_{t-4}$$

Figure D.10 displays the model's impulse responses to a news shock. Fertility rises in response to good news due to an expected wealth effect. Hours fall and leisure rises on impact, as is observed empirically. However, output contracts slightly on impact, inconsistent with empirical evidence. It is well known that many variants of the neoclassical growth model fail to generate a boom in response to higher expectations of future TFP (see e.g. Sims 2011). Much of the literature finds a strong contractionary effect on hours, investment, and output, such that "good news about tomorrow generates a recession today". Positive news makes agents wealthier. In turn, wealthier agents want to enjoy more leisure, so they reduce their labor supply today and output falls as a result. Consumption rises at all periods due to consumption smoothing. Lower output but higher consumption means investment today drops. Wages go up in the future, causing a substitution effect which counteracts the positive news wealth effect. By contrast, the model by Beaudry and Portier (2006) was the first to generate an expansionary response to "good news" shocks. Christiano et al. (2010) and Jaimovich and Rebelo (2009) propose models that produce comovement in output and employment due to a large enough intertemporal substitution in the supply of labor that compensates the negative wealth effect on labor of the news shock.

Finally, it is also worth noting that introducing children in the basic RBC model alters the response of labor supply to aggregate economy shocks. When the income effect dominates and fertility is procyclical, couples choose to have children during booms, and women reduce their labor supply. Thus female hours become less procyclical, dampening business cycle fluctuations. When instead the substitution effect dominates and fertility is countercyclical, couples prefer to have children during recessions, when the opportunity cost of their time is lower. This acts as an amplifying effect for business cycles. In this simple RBC model the cyclicality of fertility matters for the amplitude of business cycles.

### 4.4.5 Sensitivity to Parameter Calibration

#### The Cost of Raising a Child

An important parameter governing the strength of the wealth effect in the response of fertility is the cost of raising children in the household budget constraint. Figures D.11 and D.12 display the impulse response functions when the cost parameter is recalibrated such that spending on children amounts to 35% ($\phi_c = 0.15$) and 5% ($\phi_c = 0.02$) of labor income respectively. These examples illustrate how the wealth effect favoring a procyclical pattern of fertility gains importance when the cost of children is higher. An increase in the child consumption cost parameter $\phi_c$ makes fertility more procyclical. Anecdotal evidence suggests two mechanisms that could have increased this parameter over time in the U.S.

First, to the extent that the cost of raising children has been rising, this would increase the procyclicality of fertility. Estimates by the USDA suggest the cost of raising a child actually fell as a percent of median household income from approximately 20% in 1960 to 30% in 2015.[13] However, the share of expenditures on education, childcare, and healthcare rose substantially (see Figure D.15). Yet, there is evidence that households may have incurred increasing expenses for children after the age of 17 associated with, for example, college tuition, making it is possible that average household expenditures on children have been rising over time. In fact, according to the U.S. Department of Education National Center for Education Statistics, average total tuition, fees, room and board fees charged for full-time undergraduate students more than doubled in real terms between 1984 and 2015.[14]

Second, and by the same token, a preference shift from the "quantity" to "quality" of children would similarly make fertility more procyclical through a stronger income effect. There is ample evidence that fertility is U-shaped, and therefore decreasing with respect to education and income for low education/income groups. Table D.3 presents regression estimates using microdata from the Current Population Survey on birth rates by age, marital status, education, and income of the mother. Figure D.16 shows that high school completion reduces the number of kids and that the birth rate is convex in the mother's years of education, such that

[13] The total cost of raising a child (until the age of 17) has risen from $202,020 in 1960 to $233,610 in 2015 in constant 2015 U.S. dollar terms, while median household incomes in real terms rose by 80% over the same period.

[14] Statistics are available on: https://nces.ed.gov/fastfacts/display.asp?id=76

the birth rates fall and then rise with education for women aged 30-35. Figure D.17 shows that the relationship between income and fertility is non-monotonic. Low income households have more children than high income households; in the middle of the income distribution the number of children per household rises with income for certain brackets and falls again; for households with income above $35,000 the fertility rate becomes inelastic with respect to income. The idea that the number of children falls with income/wealth suggests a possible preference for *quality* rather than *quantity* of children and that such households prefer to have fewer kids and spend more on each one, than to have more kids and spend less on each.[15] As education and income rise for the lower quantiles of the population we could observe such preference shifts.

**Female Leisure Utility Function**

Another key parameter affecting the cyclical response of fertility is the exponent of female leisure in the couples' utility function. The lower the exponent is, the more fertility rises in response to transitory TFP shocks, i.e. the more procyclical fertility becomes. Figure D.13 plots impulse responses considering a logarithmic function for the utility of leisure (a special case of constant relative risk aversion utility) as specified in Doepke et al. (2007). The income effect becomes stronger relative to the intertemporal substitution effect. Fertility experiences a small drop on impact and substantial increase thereafter, in response to a transitory TFP shock. Figure D.14 shows how the functional form differs from the baseline specification around the steady state leisure of 0.65.

## 4.5 Conclusion

This paper studies the cyclical response of household fertility decisions. Fertility is shown to behave procyclically with respect to current economic conditions, with fertility falling in response to sudden increases in unemployment. Furthermore, news shocks – both inherent in consumer confidence and stock prices – are shown to be important determinants of fertility. Households respond to positive information about the future economy by increasing fertility. These news

[15] I cannot, however, exclude possible causality in the opposite way, whereby households with more children earn less income because of forgone wages due to the mother's childbearing and time away from the labor market.

shocks anticipate persistent economic expansions (drops in unemployment and increases in TFP, respectively), which give rise to large wealth effects that prompt more childbearing. By contrast, transitory surprise TFP shocks, which give rise to large intertemporal substitution and small wealth effects, lead households to decrease fertility.

These empirical findings can be matched qualitatively in an RBC model that incorporates household fertility decisions. The model furthermore highlights key channels that shape the cyclical response of fertility. First, more persistent shocks to TFP generate larger wealth effects, thereby making fertility more procyclical. Second, a higher fixed cost of children in the budget constraint amplifies the income efffect and causes fertility to become more procyclical even with respect to transitory shocks. Third, the functional form governing female utility of leisure plays an important role in determining the relative income and substitution effects.

Another important dimension, which is not considered in the current analysis, is the impact of credit constraints for the cyclicality of fertility. We can envision a world in which optimal fertility is countercyclical, such that the substitution effect dominates. Women supply labor when times are good (employers demand more labor and the opportunity cost of not working is higher) and choose to have kids and work less in economic downturns (employers demand less labor and the opportunity cost of not working is lower). With perfect access to credit, and for a given level of lifetime wealth, couples can simply postpone childbearing to economic downturns, such that they work when wages are higher rather than lower. Whereas under perfect credit markets one would expect fertility to be countercyclical, under imperfect credit markets a procyclical pattern for fertility would arise. In this context, credit markets imperfections affect the timing of having children in a suboptimal manner. This extension is closely related to the literature associating education to the business cycle, in particular on the cyclicality of education enrollments, for which a similar income versus substitution effect trade-off arises. Dellas and Koubi (2003) find that an imperfect capital market "favors a procyclical pattern" for education demand, as the credit constraints (income) effect of a recession is more likely to pose a problem for investing in education.

In fact, anecdotal evidence suggests a similar "credit constraint" channel can be at play for household fertility choices. For example, a survey of young Americans in 2011 revealed that approximately 30% of respondents claimed that the economy led them to delay starting a family.[16] Moreover, there is some supporting evidence that relaxing household credit constraints prompts an increase in fertility. One approach is to look at house price increases, which tend to relax credit constraints for home owners. Lovenheim and Mumford (2013) find that positive housing wealth shocks raises fertility among home owners, whereas the effect is insignificant among renters in the US. I find similar results using US county-level data on fertility rates, personal income, and house prices for the years 2003-2013. Tables D.4-D.6 show that lagged house prices increase fertility rates for several age groups of white, African American, and Asian women aged 15-44, using county and year fixed effects and controlling for household income[17]. Another approach is to look directly at household debt ratios as a proxy for restricted access to new credit. Using county-level fertility, personal income, and median household debt-to-income ratio[18] for the years 2001-2007, I find that a high debt burden (lagged debt leverage) reduces fertility for most age groups across women of all races. Results are reported in Tables D.7-D.9.

An interesting extension to this paper would be to study the role of credit constraints in household fertility choices. For example, fertility can rise with income due to a wealth effect. However, if fertility also rises for highly transitory income shocks, this could provide evidence in favor of a "credit constraints" story. Furthermore, households who receive positive news about future TFP would, in theory, choose to increase fertility in the absence of credit constraints. However, credit-constrained households would be unable to do so for financial reasons, preventing such households from increasing fertility in response to TFP. Therefore, the credit constraint hypothesis could be tested by redoing the empirical analysis using fertility rates for credit-constrained households. Evidence in favor of this hypothesis should find fertility to rise less in response to news shocks, and fall less in response to transitory TFP shocks. To the extent that credit constraints are playing a role in leading to suboptimal fertility choices, it would be important to shed light on this further.

[16]Source: http://www.statista.com/statistics/232195/impact-of-economy-on-major-life-decisions-for-young-americans/

[17]County-level data sources are respectively: Center for Disease Control for fertility, Bureau of Economic Analysis for personal income, and Federal Housing Finance Agency for house prices. Certain age groups are not significant though the sign is always positive, with the exception of African American women aged 40-44.

[18]Data on county-level median household debt-to-income ratio is obtained from Mian and Sufi (2009).

# Chapter 5

# Do Labor Market Institutions Matter for Fertility?

*Joint with Andrea Camilli*

## 5.1 Introduction

Starting in the 1960s, the majority of OECD countries experienced a significant reduction in fertility rates. During the same period, many countries adopted significant policies favoring fertility, making it important to understand which forces contributed to the evolution in fertility rates. In this paper we investigate whether *labor market institutions* (LMIs) that are not targeted to family-building, have an impact on fertility. Indeed a recent strand of the literature has shown that fertility became pro-cyclical in many countries starting in the mid-1990s, suggesting that there could have been changes in the economic framework that contributed to this fact.

Fertility decisions are affected by the possibility of large income shocks. Labor market institutions, to the extent that they affect volatility of unemployment and wages, may indirectly impact the level of fertility and its responsiveness to business cycles. *Employment rigidities* (ER), restricting flows in and out of employment, reduce the volatility of unemployment. *Real wage rigidities* (RWR) instead restrict wage movements and lead firms to adjust employment by more in response to shocks. In this way, real wage rigidities amplify the response of real business cycles to shocks, whereas employment rigidities act by dampening them. To the best of our knowledge, this channel, whereby LMIs affect fertility through the volatility of unemployment and real wages, has not previously been studied in the literature. This mechanism has relevant policy implications, whereby labor market reforms could indirectly affect household fertility decisions.

Using annual data for 20 OECD countries over the period 1961-2014, we study how the evolution of labor markets have impacted the *total fertility rate* (TFR). We control for the elements that can directly affect the fertility rate, such as maternity benefits, family allowances, female labor force participation, the gender wage gap, and economic conditions such as the unemployment rate and GDP growth. In our empirical analysis we compute the principal components of a large set of labor market institutions, which represent both employment rigidities and real wage rigidities. This approach allows us to reduce the number of regressors and consider the impact of interactions and combinations of institutions, having interpretable results.

Adopting panel regression analysis we find that the overall effect of labor market rigidities on fertility is the result of two opposing forces: wage and employment frictions. Considering specific groups of LMIs we find that *employment protection legislation* (EPL) and *union strength* (UnS) are positively correlated with fertility, whereas *wage bargaining centralization* (WB) and *unemployment benefits* (UB) are negatively correlated with fertility. These findings can be explained by the following facts: (i) EPL represents a clear employment rigidity that tends to reduce the volatility of employment; (ii) UnS can potentially adhere to bargaining over wages or employment (manning ratios)[1] and while we take an agnostic stance our empirical evidence suggests the latter effect dominates; and (iii) WB and UB act as real wage rigidities, which have been found to increase the volatility of employment. Unemployment benefits may act as an imperfect substitute to maternity benefits but may also affect the reservation wage of workers, limiting de-facto real wage adjustments, and encouraging flows into and out of employment. Since fertility decisions are largely affected by the risk of becoming unemployed, we expect that unemployment volatility could have a negative impact on fertility.

Our paper contributes to the existing literature by taking a wider perspective on the analysis of fertility decisions that examines the role of labor market institutions not targeted to fertility. For example, we do not consider unemployment

[1] Petrakis and Vlassis (2000) find that if unions' power is sufficiently high, they bargain solely over wages supporting the right-to-manage model hypothesis; otherwise they bargain over both wages and employment.

benefits just as a possible substitute to maternity benefits and allowances, but we investigate its impact on labor income risk and volatility. Another contribution of this paper is the collection of data for 20 OECD countries for a time period of more than 50 years, which allows us to control for potential country fixed effects or period-specific dynamics of fertility rates.

Finally, in order to better explain our empirical results and to be able to analyze policies we construct a theoretical model that incorporates household fertility decisions as in Lagerborg (2016) as well as detailed labor market frictions as in Abbritti and Fahr (2013).[2] Children provide households with direct and durable utility, but also entail two types of costs: (i) a consumption cost that enters the household budget constraint, and (ii) a time cost for women in terms of time away from work and leisure. Finally, the decision to have children is irriversible, i.e. births are non-negative.[3] Our model also has search and matching frictions in the labor market and Nash bargaining over wages and hours. We include Rotemberg-type adjustment costs for wages and employment with an asymmetric component that creates downward rigidity. Downward wage rigidity amplifies the business cycle contraction in response to negative demand shocks, with sizeable effects on unemployment and fertility in the short run and a drop in long-run fertility rates.

The rest of the paper is organized as follows. Section 5.2 discusses the literature related to this work. Section 5.3 describes the data for fertility, labor market institutions and the covariates used in our empirical analysis. Section 5.4 presents the empirical results from our regression analysis. Section 5.5 outlines our DSGE model with household fertility decisions and labor market frictions. Section 5.6 describes the model calibration and dynamics. Finally, Section 5.7 provides concluding remarks.

## 5.2 Related Literature

The literature related to this paper can be divided broadly into three groups. The first strand, represented by Easterlin (1961), Erosa et al. (2002), Doepke et al. (2007), and Doepke and Kindermann (2014) among others, studies household fertility decisions and tries to explain the pattern of fertility rates post World War II.

[2] Model results are preliminary and may change in the next version of our working paper.

[3] This occasionally binding constraint is not currently implemented in our model. We expect to include this in the next version of our working paper.

The second group is one that analyzes the evolution and dynamics of female labor force participation and how this impacts fertility, in particular Ermisch (1988), Fernandez et al. (2004), Orazio Attanasio (2008), Jones et al. (2008), Fernandez and Fogli (2009), Fogli and Veldkamp (2011) and Olivetti (2013).

Finally, this paper is related to the literature that studies the impact of labor market frictions on the volatility of macroeconomic outcomes, such as Rumler and Scharler (2009), Abbritti and Weber (2010), Merkl and Schmitz (2011), Faccini and Bondibene (2012), Abbritti and Fahr (2013), and Gnocchi et al. (2015). This literature has found that employment rigidities tend to reduce the volatility of unemployment, without significantly affecting real wages, whereas real wage rigidities increase the volatility of unemployment. We exploit the results of this literature to identify a channel that links labor market institutions with fertility decisions. In particular, Abbritti and Weber (2010) investigate the importance of labor market institutions for inflation and unemployment dynamics. They divide LMIs between those responsible for *employment rigidities* (ER) and those that cause *real wage rigidities* (RWR), since these two types of institutions may have opposite dynamic effects on macroeconomics outcomes. If ER and RWR are complements their opposite effects tend to cancel each other out, since a high degree of ER is associated with lower unemployment volatility and high RWR are associated with high unemployment volatility. If instead they are substitutes, there could be an amplification effect. The authors find that a higher degree of employment rigidities reduces the volatility of unemployment and vacancies but increases the volatility of real wages. On the other hand, real wage rigidities increase the volatility of unemployment. Faccini and Bondibene (2012) instead investigate the impact of nine labor market institutions on unemployment volatility, finding that some LMIs matter for unemployment dynamics over the business cycle. Finally, Gnocchi et al. (2015) find that more flexible labor institutions are associated with lower business cycles and lower unemployment volatility.

In this paper we want to take a broader perspective with respect to the existing literature on fertility, in order to consider an aspect that quite surprisingly has been largely ignored by the literature that investigates fertility dynamics: the legal framework of labor markets. Hence our work does not focus only on the main drivers of fertility that have been analyzed by the existing literature, but it considers additional elements that may impact the decision of having children, such as employment volatility and real wage volatility. The papers that are closest to our work are Adsera (2004) and Adsera (2011), which analyze the role of maternity benefits and allowances for fertility decisions, controlling for the impact of unemployment benefits, employment protection and share of public employment. In this paper we use a much wider set of labor market institutions and we also take into account their combinations and interactions.

## 5.3 Data

We collected annual data from 1961 to 2014 for 20 OECD countries using different sources.[4] The time period we consider is long enough to analyze both business cycle fluctuations and the long-run trend in the total fertility rate. Moreover we analyze a relatively large sample of countries in order to account for possible country-specific differences in fertility. The countries included are: *Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland United Kingdom and United States*.

### 5.3.1 Total Fertility Rate

Our variable of interest is the *total fertility rate* (TFR), defined as "the total number of children that would be born to each woman if she were to live to the end of her child-bearing years and give birth to children in alignment with the prevailing age-specific fertility rates". The measure of TFR that we use in our main analyses is from the OECD Health Database. Figure E.1 shows the evolution of TFR from 1960 to 2014 for each of the countries considered. There has been a general downward trend in TFR between the 1960s and the 1970/80s, after which the total fertility rate stabilized. Figure E.2 presents the average value of TFR in the period considered (red diamonds) as well as its dynamics over time (blue circles). This shows more clearly how some countries that started with a very high TFR, such as Canada or Ireland, converged towards lower levels, while other countries that already had a low TFR, such as Japan or Sweden, experienced a smaller evolution over the last 50 years.

[4] All variables are plotted in the Appendix.

For robustness, we also consider the birth rate measured as number of births per 1000 women aged between 15 and 49, obtained from the OECD.[5] Figure E.1 shows that birth rates follow a very similar path to TFR. Birth rates have been steeply decreasing for age group 20-24 and increasing for age group 30-34, reflecting fertility postponement. Figure E.3 shows birth rates for different age groups. Women in age groups 15-19 and over 40 have very low birth rates in all countries considered.

### 5.3.2 Labor Market Institutions

We gathered data describing labor market institutions from the OECD and the Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts (ITCWSS) database. We have variables that represent both employment rigidities and real wage rigidities. In particular, we consider the set of LMI indicators described in Table E.1. Table E.2 provides descriptive statistics for each LMI. Figures E.12-E.22 show the evolution of each LMI by country and over time. Employment protection legislation shows very little variation for most countires, with few exceptions such as Germany, Italy, Portugal, Spain, and Sweden, which experienced substancial reductions in protection. Union density, coverage, and concentration faced more heterogeneous changes in the last decades, with some countries increasing and others decreasing the strength of unions. Institutions that affect real wage rigidities include the centralization and level of wage bargaining, government intervention in the bargaining process, the extension of collective agreements, and the minimum wage. We see substantial variation in wage bargaining centralization and government intervention. We observe a general reduction in the minimum wage for countries such as Ireland, Japan, the Netherlands, Spain, and the UK. Unemployment benefits are defined as an average of benefit replacement rates and generally have displayed an increase in generosity since 1960.

[5]The starting year for data on birth rates by age groups is later for some countries in our sample, namely: Norway in 1961, New Zealand in 1962, Sweden in 1968, US in 1970, Spain in 1971, UK in 1973, France in 1998, and Canada and Germany in 2000.

### 5.3.3 Control Variables

As control variables, we want to account for all other factors that can affect the fertility decision. First, we control for maternity benefits and family allowances that are related to maternity or paternity. This is necessary in order to be able to disentangle the effect between labor institutions targeted to fertility and those that do not specifically target fertility decisions. We obtain this data from Gauthier (2011) for the period 1960-2010 and extend it until 2014 using the same data source, compiled from Social Security Programs Throughout the World and the Council of Europe. Second, we control for economic conditions such as GDP growth (obtained from the World Bank's World Development Indicators), unemployment rate (obtained from the IMF Economic Outlook and Gauthier (2011)), and the NAIRU (obtained from the OECD). These are important as empirical studies have found that fertility relates to the business cycle (e.g. Lagerborg, 2016). Finally, we also control for gender differentials such as female labor force participation and the gender wage gap, constructed using male and female wages obtained from the OECD. Table E.3 provides descriptive statistics for our control variables.

### 5.3.4 Principal Component Analysis

In order to take into account the effects of combinations and interactions among labor market institutions, we adopt *principal component analysis*. This allows us to include a large number of LMIs in our estimates, reducing possible omitted variable bias, and at the same time allowing to save degrees of freedom and to have interpretable results from our empirical analysis. We divide LMIs on the basis of economic meaning, into four different groups of rigidities: (i) employment protection, (ii) union strength, (iii) wage bargaining, and (iv) unemployment benefits. For each group, we compute principal components that we call *LMI Factors*.

We also construct principal components of the control variables for the same reasoning. In particular we calculate one component for maternity benefits, one for economic conditions and one for the gender gap. In total we get three principal components that we call *Principal Controls*.

#### 5.3.4.1 LMI Factors

We divide the LMI indicators into four groups, on the basis of economic reasoning: employment protection legislation (EPL), union strength (UnS), wage bargaining centralization (WB), and unemployment benefits (UB). EPL is the principal component combining employment protection legislation on permanent and temporary contracts. UnS summarizes union density, coverage, and concentration. We classify EPL and UnS as *employment rigidities* (ER).[6] WB comprises the centralization and level of wage bargaining, government intervention in the bargaining process, the extension of collective agreements, and the minimum wage. UB is defined as an average of benefit replacement rates and acts both as a substitute to maternity benefits but also increases the reservation wage, affecting employment inflows and outflows. In our framework both WB and UB are representative of *real wage rigidities*. Table E.4 shows the correlation between the four LMI Factors and the original labor market institutions.

#### 5.3.4.2 Principal Controls

We calculate three principal components that we use as control variables. One principal component combines maternity benefits and family allowances, which we label *PC maternity*. Another principal component combines GDP growth, the unemployment rate, and NAIRU, which we label *PC economy*. Finally, we create a principal component for the gender gap, combining female labor force participation and the wage gap, which we label *PC gender*. Table E.5 shows the correlation between the three principal controls and the original covariates.

## 5.4 Empirical Results

### 5.4.1 Panel Regression Analysis

In this section we document the correlation between LMIs and the total fertility rate. In order to exploit both the cross-sectional and over-time variation of the data, we use panel regression analysis with country fixed effects, year fixed effects,

[6] The union strength factor could theoretically be included in either group, depending on the role of unions in increasing employment protection or limiting downward adjustment of wages. A priori we do not take a stance on this but our empirical evidence seems to suggest that unions act mainly as an employment rigidity.

and country-specific time trends. Country fixed effects account for the fact that there may exist country-specific preferences for fertility. Year fixed effects account for average fertility changes across years. For example, it takes into account the clear downward trend in fertility rates observed before the 1980s. Finally, the country-specific time trend allow for trends to vary across countries. Our baseline regression reads:

$$TFR_{i,t} = \alpha + \beta' \mathbf{LMI}_{i,t} + \gamma' \mathbf{X}_{i,t} + \mu_i + \nu_t + cstt_{i,t} + \varepsilon_{i,t}$$

where $TFR_{i,t}$ is total fertility rate in year $t$ in country $i$, $\alpha$ is a constant, $\mu_i$ are country fixed effects, $\nu_t$ are year fixed effects, and $cstt_i$ represent the country-specific time trends. $\mathbf{LMI}_{i,t}$ is the vector of labor market institutions or their principal components. $\mathbf{X}_{i,t}$ represents the set of principal components derived from the original control variables and is the same for all specifications.

#### 5.4.1.1 Evidence from Principal Components

Table E.6 shows the panel fixed effects regression estimates using the four LMI Factors. Column (1) represents our preferred model, while columns (2)-(5) present results including one LMI Factor at the time. From column (1), we can see that EPL and UnS, both employment rigidities, are positively correlated with fertility. The fact that EPL has a positive impact on fertility is not surprising since employment protection increases the perception of economic stability of households and reduces the volatility of employment. The positive sign for union strength can be explained by the fact that unions work for preventing large employment adjustments, acting then as an employment rigidity. WB and UB instead, are negatively correlated with fertility, and behave as real wage rigidities. WB tends to reduce the volatility of wages at the expense of increasing the volatility of employment, having a negative impact on fertility. The negative sign for UB suggests that its role is more similar to a real wage rigidity than to a substitute for maternity benefits. By comparing the first column with the others, we find that results are robust to considering one factor at a time.

By decomposing the effects of each LMI factor, we observe that wage bargaining rigidities drive most of the variation in TFR (see Figure E.4).[7] Among the employment rigidities, union strength appears to be the most relevant. We can furthermore see the effects played by our control variables (see Figure E.5). Economic conditions and maternity benefits seem to play a major role in impacting fertility. Gender inequality appears to be less important, but consistently slightly depresses fertility, consistent with diminishing gender gaps.

#### 5.4.1.2 Evidence from Individual LMIs

Looking at individual LMIs, panel regression results confirm that rigidities related to employment have a positive effect on fertility, whereas rigidities related to wages affect fertility negatively (see Table E.7). EPL for permanent contracts appear to favor fertility, whilst this rigidity has no significant effect for temporary contracts (columns 1-2). Rigidities related to union strength are positively correlated with fertility with the exception of union coverage (columns 3-5). It is possible that union coverage does not translate to higher employment rigidity if collective agreements are wage-related.

Wage rigidities appear to depress fertility. More rigid wage bargaining—as measured by the degree of government intervention, the level at which bargaining takes place, the extension of collective agreements, centralization of wage bargaining, and the minimum wage—is negatively correlated with fertility (columns 6-11). As aforementioned, unemployment benefits may act as a substitute to maternity benefits but they can also increase the reservation wage of workers, acting as a downward wage rigidity, and this could explain the negative correlation found with fertility (column 12).

#### 5.4.1.3 Robustness: Evidence from Birth Rates by Age

As a robustness check, we repeat the same analysis using birth rates (per 1,000 females) by age groups. Regression results using average birth rates are very similar to TFR (see Table E.9). Signs and significance are robust for most age groups.

[7]We also compute the first principal component considering all labor market institutions together at once, representing a measure of overall rigidity of the labor market. We robustly find that more rigid labor markets are associated with lower total fertility rates. This finding is consistent with the notion that an overall more rigid labor market leads to higher volatility in unemployment and business cycles more generally (Gnocchi et al., 2015). Results are available from the authors upon request.

Looking at LMI factors, results are in line with our main estimation (see Table E.8). Employment rigidities carry a positive sign for all age groups except: EPL for age groups 30-34 and 45-49 (where the latter is insignificant) and UnS for age group 15-19.[8] Real wage rigidities are even more robust: all age groups have the correct sign. More rigid or centralized wage bargaining tends to reduce birth rates. Unemployment benefits also robustly reduce birth rates.

Considering individual LMIs, results for average births again remain robust. We obtain that EPL is significant for permanent contracts, confirming robustness of our results using TFR. Whereas EPL on permanent contracts shifts births from older to younger cohorts (under 30), EPL has the opposite effect on temporary contracts. LMIs governing the strength of unions have a positive effect on birth rates.[9] Wage bargaining rigidities and the unemployment benefit depress birth rates. We note that the youngest cohort, aged 15-19, seems to respond differently to several labor market institutions, with opposite signs to other age groups.

#### 5.4.1.4 Robustness: Alternative Specifications

We conduct several robustness checks with respect to alternative specifications (see Table E.11). We consider a specification that omits the country-specific time trend (column 2). We also consider a generalized least squares specification that corrects for potential country-specific serial correlation in residuals (column 3). Finally, we implement Wild Cluster Bootstap that corrects standard errors for the small number of country clusters (column 4). Coefficient signs and significance remain mostly robust, although significance is largely reduced when implementing the Wild Cluster Bootstrap procedure.

As an additional robustness check, we assess whether the results depend on our use of specific principal controls. As a first alternative specification, we estimate panel regressions with a principal component for maternity, which separately includes maternity benefit length and generosity, and family allowances for different number of children. Finally, in order to exclude the possibility that the use per se of principal component analysis is driving our results, we perform the

[8] EPL appears to shift births towards younger age groups (higher coefficients for younger cohorts). On the other hand, union strength appears to reduce birth rates only for the youngest cohort (ages 15-19), who might not reap benefits from union negotiations over higher pay and number of employees.

[9] Union coverage, which had a negative sign for TFR, here is insignificant. However, we see that union coverage shifts births from younger to older cohorts.

same empirical analysis using directly the eight control variables which were used to compute the three principal controls. The results under these two alternative specifications are very similar with respect to those of our baseline model.[10]

We conduct a final robustness check with respect to the timing of fertility and institutional change. Changes in institutions may take time to be implemented and tend to be announced in advance. Our baseline specification, in which we consider TFR at time $t$, considers announcement effects. If institutions are announced in advance and if fertility responds to such annoucements, a contemporaneous regression should capture this since TFR at time $t$ will be affected by announcement in $t-1$ of institutional change at time $t$. If we instead disregard announcement effects, we would expect institutions announced and implemented at time $t$ to affect household fertility decisions taken contemporaneously, which would show up in data on fertility and birth rates at time $t+1$. Results remain consistent considering both timings, even when using lead fertility (see Tables E.10 and E.12).[11]

## 5.4.2 Investigating the Mechanism

### 5.4.2.1 Volatility of Wages and Unemployment

Fertility decisions are affected by the possibility of large income shocks. As a result, movements in wages may affect household fertility decisions. Even larger income shocks are generated by unemployment. The unemployment rate, proxying for the probability of becoming unemployed, is expected to detriment fertility. Similarly, unemployment volatility generates fluctuations in this probability of unemployment, and hence potential fluctuations in income.

We use panel regressions with country and time fixed effects to explore the effect of unemployment and wage volatility on fertility outcomes. To obtain measures of volatility, we collapse the data into decadal frequency and compute the standard deviation of unemployment and wages over the decade.[12] This reduces

[10]The tables with the results of these robustness checks are available upon request.

[11]One potential concern regards endogeneity. There could, for example, exist a political economy effect through which high fertility leads society to want more employment protection. For the next version of this working paper we hope to include evidence such as including more lags and leads of LMIs.

[12]In our main estimates we use average male wages to compute the volatility of nominal and real wages. Results are also robust to using female wages and the average of male and female wages.

our sample from approximately 1,000 observations to 120 observations (6 decades for 20 countries), making statistical significance more difficult to obtain.

Table E.13 investigates the role played by volatility in unemployment, in real/nominal wages, and in expected wages, as well as the level of the unemployment rate, in affecting the total fertility rate.[13] We find that unemployment volatility negatively correlates with fertility (column 1) whereas real and nominal wage volatility (columns 2 and 3) positively correlate with fertility. The combined effect of wage and unemployment volatility can be analyzed by considering the volatility of expected real wages, defined as the product of real wages and the employment rate (one minus the unemployment rate). Volatility in expected real wages is detrimental to fertility (column 4).

We interpret this as suggestive evidence that income risks associated with unemployment outweigh those associated with wage fluctuations in shaping household fertility decisions. Higher unemployment volatility is detrimental to fertility. By contrast, higher wage volatility means firms can adjust wages rather than employment, thereby reducing the large income risks associated with unemployment. Thus, we expect that more flexibility in LMIs governing employment rigidities, allowing for higher unemployment volatility, reduces fertility. In contrast, more flexibility in LMIs governing wage rigidities, allowing for higher volatility of wages, should increase fertility.

To investigate this hypothesis we estimate the effect of labor market institutions on volatility of unemployment, wages, and expected wages (see Table E.14). We find that ERs such as EPL on permanent contracts reduces volatility of employment and expected wages, while increasing volatility of real wages. By contrast, RWRs such as centralized wage bargaining and unemployment benefits reduce the volatility of real wages, at the expense of higher volatility of employment and expected wages.

Another discussion worth having is on the role of unemployment volatility versus unemployment levels. A higher unemployment rate translates into a higher overall probability of being unemployed. Higher unemployment volatility, on the other hand, does not necessarily translate into a higher risk of unemployment. Instead it reflects higher uncertainty over the probability of unemployment.

[13]Results are robust to using birth rates and to including maternity, economy, and gender principal controls. We exclude the economy principal control from specifications that include the level of unemployment, namely columns 6-8. Results are available from the authors upon request.

This leads us to question what matters for fertility: is it the unemployment rate in levels or its volatility? Both seem to matter as can be seen in Table E.13. Higher volatility of unemployment and higher unemployment rates both reduce fertility (columns 1 and 5). This result is robust to including both variables together (column 6).

#### 5.4.2.2 Two Stage Least Squares

One channel through which labor market institutions may affect fertility outcomes is through the volatility of unemployment, wages, and expected wages. In order to study this channel, we employ a *two stage least squares* (2SLS) estimation in which LMIs act as instruments for volatility. We expect employment rigidities, such as EPL and UnS, to reduce the volatility of unemployment (while allowing for higher volatility of wages) and thereby increase fertility. Real wage rigidities, such as WB and UB, are expected to reduce the volatility of wages at the expense of higher volatility of unemployment, thereby reducing fertility.

We remain cautious in interpreting results as evidence in favor of our hypothesized channel. To the extent that there may exist other channels through which labor market institutions affect fertility, which are correlated with our measures of volatility of unemployment and wages, our results may also be capturing these other channels. This could happen, for example, if LMIs affect the level of expected wages and unemployment, which in turn affect fertility. In other words, we cannot exclude the fact that there may be other channels acting that our simply correlated with ours. The evidence presented here should be thought of as *not excluding* the possibility of our channel, rather than *proving* our channel.

We find scattered evidence that these predicted results are consistent with the data. Table E.15 presents results for our estimations using two stage least squares.[14] The first channel we consider is whether labor market rigidities affect fertility through the volatility of unemployment (columns 1-4). The LMI factors yield no significance with the exception of UB. This may be due to the small sample size making it difficult to obtain statistical significance. We thus turn to evidence from individual LMIs, three of which yield significant results.[15]

[14] All results are robust to using birth rates instead of TFR. Results are avialable from the authors upon request.

[15] No significance is obtained for LMIs relating to union strength.

EPL relating to permanent contracts[16] is found to reduce unemployment volatility and thereby increase fertility (column 1). Wage bargaining centralization and unemployment benefits, both considered real wage rigidities, on the other hand increase unemployment volatility thereby reducing fertility (columns 2-3). In the first stage of the regression, each of these LMIs when considered separately matters in explaining unemployment volatility, however when all three LMIs are included, we lose significance possibly because of the small sample size. In the second stage, we observe that the unemployment volatility induced by these LMIs is detrimental for fertility. This two-stage analysis thus shows us that to the extent that these labor market institutions affect the volatility of unemployment, they also affect fertility.

Second, we study the channel by which LMIs affect fertility through real wage volatility (columns 5-8). The effect of LMIs through the volatility of wages carries the opposite sign. To the extent that LMIs increase real wage volatility, this has a positive effect on fertility. Employment protection on permanent contracts increases the volatility of real wages whereas more centralized (rigid) wage bargaining reduces real wage volatility. Unemployment benefits, despite having the predicted (negative) sign, have no significant effect on real wages.

Finally, we analyze the combined effect of unemployment and wages by studying the channel whereby LMIs affect fertility through the volatility of expected wages (see Table E.16). Estimates carry the same sign as in the unemployment volatility channel.

## 5.5 DSGE Model

In order to study how labor market institutions can affect household fertility, we build a DSGE model with enough features to describe the household's fertility decision as in Lagerborg (2016) but also the heterogenous impact of different labor market institutions. In particular, in our model children are irriversible (i.e. births are non-negative) and provide households with direct and durable utility, but also entail two types of costs: (i) a consumption cost that enters the household budget constraint, and (ii) a time cost for women in terms of time away from work and

[16] EPL relating to temporary contracts has no effect.

leisure. We also include several labor market frictions: search and matching frictions in the labor market, Nash bargaining over wages and hours, firm vacancy posting costs, and Rotemberg-type adjustment costs for wages and employment with an asymmetric component that creates downward rigidity. In particular we are interested in labor market frictions that have an empirical counterpart: (i) the separation rate (related to EPL), (ii) the unemployment benefit, and (iii) parameters governing wage and employment adjustment costs, which can be compared to RWR and UR more generally.[17]

### 5.5.1 The Labor Market

Search and matching frictions generate unemployment in a labor market that is divided into two segments based on gender, in which females and males can be denoted respectively by $i = F, M$. Job seekers $u_t^i$ and firm vacancies $v_t^i$ need to match to become productive, following a constant returns to scale matching technology. We denote by $q_t^i$ the probability for a firm to fill an open gender-specific vacancy and by $f_t^i$ the probability for a female or male worker to find a job. An exogenous fraction $s$ of jobs is destroyed each period and new gender-specific matches $m_t^i$ become operative in the same period. The unemployment rate $ur_t^i$ is the fraction of female and male workers without employment after the matching process has taken place.

Matching:

$$m_t^i = \overline{m}(u_t^i)^{\zeta}(v_t^i)^{1-\zeta}$$

Job-seekers:

$$u_t^i = 1 - (1-s)e_{t-1}^i$$

Job-filling:

[17] Other parameters that relate to labor market frictions include vacancy posting costs and matching function efficiency, both corresponding to employment rigidities. Employment rigidities correspond to parameters: $\chi_e$, $\psi_e$, $s$, $\kappa$, and $\overline{m}$, whereas real wage rigidities correspond to parameters: $\chi_w$, $\psi_w$, $\eta_i$, and $b$. Note that we do not yet have model counterparts for union strength nor the centralization of the wage bargaining process, and that worker bargaining power is not an adequate proxy. Nash bargaining, calibrated to standard parameters, induces too much volatility in wages (highly procyclical movements reflecting high worker bargaining power), which dampens the cyclical movement in firms' incentives to hire. Therefore, a high value for worker bargaining power $\eta_i$ traslates into more flexible wages.

$$q_t^i = \frac{m_t^i}{v_t^i} = \overline{m}\left(\frac{v_t^i}{u_t^i}\right)^{-\zeta}$$

Job-finding:

$$f_t^i = \frac{m_t^i}{u_t^i} = \overline{m}\left(\frac{v_t^i}{u_t^i}\right)^{1-\zeta}$$

Employment:

$$e_t^i = (1-s)e_{t-1}^i + v_t^i q_t^i$$

Unemployment rate:

$$ur_t^i = 1 - e_t^i$$

### 5.5.2 Household Optimization

The representative household, consisting of a female and male member[18], jointly maximizes lifetime expected utility subject to its budget constraint. Consumption is pooled inside the household to perfectly insure against employment fluctuations. Utility is derived from consumption $c_t$, leisure of the female $l_t^F$ and male $l_t^M$, and children $n_t$. Households earn income from wage labor, unemployment benefits $b$ and interest on bonds $a_t$. Females and males work $h_t^i$ hours at wage $w_t^i$, where the employment rate is $e_t^i$. Households optimize consumption, bond holdings, and fertility at each period. The number of children in the household follows a decay of $\delta_n$, which represents the proportion of children reaching adulthood in each period, akin to models of probabilistic ageing (Gertler, 1999). The number of new births is non-negative, such that having children is an irriversible decision and has long-lasting utility and costs. The household optimization problem can be expressed as:

$$\max_{c_t,a_t,n_t} E_0 \sum_{t=0}^{\infty} \beta^t u\left(c_t, l_t^F, l_t^M, n_t\right) = \max E_0 \sum_{t=0}^{\infty} \beta^t \left\{ \ln(c_t) - \sum_i \sigma_l^i \frac{\left(h_t^i\right)^{1+\xi}}{1+\xi} e_t^i + \sigma_n \ln(n_t) \right\}$$

[18]Each household is thought of as a continuum of members along the unit interval.

s.t. BC:

$$c_t + \phi_c n_t + \frac{a_t}{p_t r_t} = \sum_i w_t^i h_t^i e_t^i + \sum_i b\left(1 - e_t^i\right) + \frac{a_{t-1}}{p_t}$$

Leisure:

$$l_t^M = 1 - h_t^M$$

$$l_t^F = 1 - h_t^F - \phi_l \left(n_t\right)^{\psi_l}$$

Number of children:

$$n_t = \left(1 - \delta_n\right) n_{t-1} + births_t$$

$$births_t \geq 0$$

where $births_t$ is the birth rate at time $t$. This problem can be rewritten as:

$$\max_{c_t, a_t, n_t} E_0 \sum_{t=0}^{\infty} \beta^t \left\{ \ln\left(c_t\right) - \sum_i \sigma_l^i \frac{\left(h_t^i\right)^{1+\xi}}{1+\xi} e_t^i + \sigma_n \ln\left(n_t\right) \right\}$$
$$+\beta^t \lambda_t \left( \sum_i w_t^i h_t^i e_t^i + \sum_i b\left(1 - e_t^i\right) + \frac{a_{t-1}}{p_t} - c_t - \phi_c n_t - \frac{a_t}{p_t r_t} \right)$$

The first order conditions with respect to consumption, bond holdings, and the number of children, respectively, yields:

$$\lambda_t = \frac{1}{c_t}$$

$$\frac{\lambda_t}{p_t r_t} = \frac{\beta E_t \lambda_{t+1}}{E_t p_{t+1}}$$

$$\frac{\sigma_n}{n_t} + \sigma_t^F \left(h_t^F\right)^{\xi} e_t^F \psi_l \phi_l \left(n_t\right)^{\psi_l - 1} = \lambda_t \left( \phi_c + w_t^F e_t^F \psi_l \phi_l \left(n_t\right)^{\psi_l - 1} \right)$$

### 5.5.3 Firms

Firms use labor (employment $e_t^i$ and hours $h_t^i$) and capital $k_t$ as inputs in a constant returns to scale production function. They choose vacancy posting $v_t^i$ and investment $i_t$ to maximize the expected sum of discounted profits given the production function, evolution of capital, and adjustment costs for wages and employment. Adjustment costs are convex and may be asymmetric, allowing for downward rigidities whereby wages and employment are more easily increased than cut. $\nu$ captures the degree of indexation of wages to the gross inflation rate $\pi_t$. Total labor supply is a constant elasticity of substitution (CES) aggregate of female and male workers, where $\rho$ determines the substitution elasticity[19] and $\theta$ is the firms' relative preference for female workers[20].

$$\max_{v_t, i_t} E_0 \sum_{t=0}^{\infty} \beta^t \left\{ \frac{\lambda_t}{\lambda_0} \left[ y_t - \sum_i w_t^i h_t^i e_t^i (1 + ACw_t^i) - \sum_i ACe_t^i - \sum_i \frac{\kappa v_t^i}{\lambda_t} - i_t \right] \right\}$$

s.t.

$$y_t = z_t k_t t^\alpha \left[ \theta \left( h_t^F e_t^F \right)^\rho + (1-\theta) \left( h_t^M e_t^M \right)^\rho \right]^{\frac{1-\alpha}{\rho}}$$

$$k_t = (1-\delta) k_{t-1} + i_t$$

$$\pi_t^{i,w} = \frac{w_t^i}{w_{t-1}^i} \pi_t$$

$$\pi_t = \frac{p_t}{p_{t-1}}$$

$$ACw_t^i = \frac{\chi_w}{2} \left( \frac{\pi_t^{i,w}}{\pi_t^\nu} - 1 \right)^2 + \frac{1}{\psi_w^2} \left( \exp\left\{ -\psi_w \left( \frac{\pi_t^{i,w}}{\pi_t^\nu} - 1 \right) \right\} + \psi_w \left( \frac{\pi_t^{i,w}}{\pi_t^\nu} - 1 \right) - 1 \right)$$

[19] The elasticity of substitution between female and male labor in production is $1/(1-\rho)$. $\rho \to 0$ represents perfect substitution, $\rho \to -\infty$ represents a Leontief production function, and $\rho \to 1$ represents the Cobb Douglas case.

[20] This gender bias in employment will determine the extent of gender discrimination in employment. $\theta = 0.5$ implies no gender discrimination, whereas firms discriminate against females when $\theta < 0.5$.

$$ACe_t^i = \frac{\chi_e}{2}\left(\frac{e_t^i}{e_{t-1}^i} - 1\right)^2 + \frac{1}{\psi_e^2}\left(\exp\left\{-\psi_e\left(\frac{e_t^i}{e_{t-1}^i} - 1\right)\right\} + \psi_e\left(\frac{e_t^i}{e_{t-1}^i} - 1\right) - 1\right)$$

Technology follows an AR(1) stochastic process:

$$\ln z_t = \rho_z \ln z_{t-1} + \varepsilon_t^z$$

$$\varepsilon_t^z \sim N\left(0, \sigma_z^2\right)$$

The first order condition with respect to vacancies yields a job creation condition. This equates expected vacancy posting costs to the value of a filled vacancy, given by revenues from output net of wages and adjustment costs for wages and employment, plus the expected continuation value of the job next period.

$$\mathbf{J}_t^i \equiv \frac{\kappa}{\lambda_t q_t^i} = MPe_t^i - w_t^i h_t^i (1 + ACw_t^i) - \frac{ACe_t^{i'}}{e_{t-1}^i} + \beta E_t\left\{\frac{\lambda_{t+}}{\lambda_t}\left[1(1-s)\mathbf{J}_{t+1}^i + \frac{ACe_{t+1}^{i'} e_{t+1}^i}{\left(e_t^i\right)^2}\right]\right\}$$

where

$$ACe_t^{i'} = \frac{\partial ACe_t^i}{\partial(e_t^i / e_{t-1}^i)} = \chi_e\left(\frac{e_t^i}{e_{t-1}^i} - 1\right) + \frac{1}{\psi_e}\left[1 - \exp\left\{-\psi_e\left(\frac{e_t^i}{e_{t-1}^i} - 1\right)\right\}\right]$$

$$MPe_t^F = \frac{\theta(1-\alpha)y_t(h_t^F e_t^F)^{(\rho-1)} h_t^F}{h_t}$$

$$MPe_t^M = \frac{(1-\theta)(1-\alpha)y_t(h_t^M e_t^M)^{(\rho-1)} h_t^M}{h_t}$$

$$h_t = \theta\left(h_t^F e_t^F\right)^\rho + (1-\theta)\left(h_t^M e_t^M\right)^\rho$$

Maximizing with respect to capital yields Tobin's Q for investment decisions (the shadow price of capital), which equates the marginal cost of investment to its expected benefit (the marginal product of capital):

$$1 = \alpha \frac{y_t}{k_t} + \beta \frac{E_t(\lambda_{t+1})}{\lambda_t}(1-\delta)$$

### 5.5.4 Nash Bargaining

Nominal wages and hours worked are bargained by maximizing the Nash product of worker and firm surpluses:

$$\max_{w_t^i, h_t^i} (\mathbf{N}_t^i - \mathbf{U}_t^i)^{\eta_i} (\mathbf{J}_t^i)^{1-\eta_i}$$

for $i = F, M$. The exogenous gender-specific bargaining power of workers is denoted by $\eta_i$ and determines how the joint surplus is shared between the worker and firm. $\mathbf{N}_t^i$ denotes the marginal value of employment, which comprises wage income net of labor disutility, plus the continuation value of being employed. $\mathbf{U}_t^i$ denotes the marginal value of unemployment, which comprises unemployment benefits plus the continuation value of being unemployed.

$$\mathbf{N}_t^i = w_t^i h_t^i - \frac{\sigma_l^i}{\lambda_t} \frac{\left(h_t^i\right)^{1+\xi}}{1+\xi} + \beta E_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} \left( [1-(1-f_{t+1}^i)s] \mathbf{N}_{t+1}^i + s(1-f_{t+1}^i) \mathbf{U}_{t+1}^i \right) \right\}$$

$$\mathbf{U}_t^i = b + \beta E_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} \left( f_{t+1}^i \mathbf{N}_{t+1}^i + (1-f_{t+1}^i) \mathbf{U}_{t+1}^i \right) \right\}$$

#### 5.5.4.1 Wages

Bargaining over the nominal wage yields an optimal sharing rule similar to the standard Nash bargaining solution:[21]

$$\omega_t^i \mathbf{J}_t^i = (1-\omega_t^i)(\mathbf{N}_t^i - \mathbf{U}_t^i)$$

with $\omega_t^i$ being the effective time-varying bargaining power of the worker:

$$\omega_t^i \equiv \frac{\eta_i}{\eta_i + (1-\eta_i)\tau_t^i}$$

and where $\tau_t^i$ reflects the evolution of current and expected wage adjustment costs:

[21] See derivations by Arseneau and Chugh (2007).

$$\tau_t^i \equiv -\frac{\partial \mathbf{J}_t^i / \partial w_t^i}{\partial(\mathbf{N}_t^i - \mathbf{U}_t^i)/\partial w_t^i} = 1 + ACw_t^i + ACw_t^{i'} \frac{\pi_t^{i,w}}{\pi_t^{\nu}} - (1-s)\beta E_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} ACw_{t+1}^{i'} \frac{h_{t+1}^i}{h_t^i} \frac{(\pi_{t+1}^{i,w})^2}{\pi_{t+1}^{1+\nu}} \right\}$$

$$ACw_t^{i'} = \frac{\partial ACw_t^i}{\partial(\pi_t^{i,w}/\pi_t^{\nu})} = \chi_w \left( \frac{\pi_t^{i,w}}{\pi_t^{\nu}} - 1 \right) + \frac{1}{\psi_w} \left[ 1 - \exp\left\{ -\psi_w \left( \frac{\pi_t^{i,w}}{\pi_t^{\nu}} - 1 \right) \right\} \right]$$

$$ACw_{t+1}^{i'} = \frac{\partial ACw_{t+1}^i}{\partial(\pi_{t+1}^{i,w}/\pi_{t+1}^{\nu})} = \chi_w \left( \frac{\pi_{t+1}^{i,w}}{\pi_{t+1}^{\nu}} - 1 \right) + \frac{1}{\psi_w} \left[ 1 - \exp\left\{ -\psi_w \left( \frac{\pi_{t+1}^{i,w}}{\pi_{t+1}^{\nu}} - 1 \right) \right\} \right]$$

In the absence of adjustment costs, $\tau_t^i$ is equal to 1, and we obtain the constant sharing rule with $\omega_t^i = \eta_i$. With adjustment costs the bargaining power becomes state-dependent. During periods of rising wages, $AC_{w,t}^{i'} > 0$, the effective bargaining power of workers decline whereas during periods of declining wages, the bargaining power of workers increase. The asymmetry in the wage adjustment cost function magnifies this effect, i.e. bargaining power increases by more in recessions than it is reduced in expansions.

The bargained wage becomes:

$$\frac{\omega_t^i \kappa}{\lambda_t q_t^i} = (1 - \omega_t^i) \left[ w_t^i h_t^i - \frac{\sigma_l^i}{\lambda_t} \frac{\left(h_t^i\right)^{1+\xi}}{1+\xi} - b + \beta(1-s) E_t \left( \frac{\omega_{t+1}^i}{1-\omega_{t+1}^i} \frac{\kappa}{\lambda_t q_{t+1}^i} (1 - f_{t+1}^i) \right) \right] \tag{5.1}$$

We can define a wage gap as:

$$\Phi_t \equiv \frac{w_t^M}{w_t^F}$$

#### 5.5.4.2 Hours

The number of hours worked also reflect bargaining between the worker and firm, optimized to maximize their joint surplus. In the absence of wage adjustment costs, the marginal rate of substitution between consumption and hours worked ($mrs_t^i = \frac{\sigma_l^i}{\lambda_t} \left(h_t^i\right)^{\xi}$) equates the marginal product of labor of an hour of work for the firm ($mpl_t^i = \frac{\partial^2 y_t}{\partial e_t^i h_t^i}$), adjusted for the relative price. Wage adjustment costs reduce hours worked by reducing net productivity, introducing a wedge between the marginal rate of substitution and the marginal product of labor (the latter needs to be higher to compensate for the deadweight loss of the adjustment cost). A second effect leads to an intertemporal reallocation of hours worked, whereby hours increase when wages are larger than the marginal rate of substitution and wages are growing. In these ways, the second term on the right captures the change in costs due to current and expected wage changes.

$$\eta_i \left( \frac{1-\omega_t^i}{\omega_t^i} \right) \left( wti - \frac{\sigma_l^i}{\lambda_t} \left( h_t^i \right)^{\xi} \right) = -(1-\eta_i) \left[ \frac{\partial MPe_t^i}{\partial h_t^i} - w_t^i(1 + ACw_t^i) \right]$$

where:

$$\frac{\partial MPe_t^F}{\partial h_t^F} = \theta(1-\alpha) y_t (e_t^F h_t^F)^{\rho-1} \left[ \frac{\rho}{h_t^{\rho}} + \theta(1-\alpha-\rho) \frac{1}{h_t^{2\rho}} (e_t^F h_t^F)^{\rho} \right]$$

and

$$\frac{\partial MPe_t^M}{\partial h_t^M} = (1-\theta)(1-\alpha) y_t (e_t^M h_t^M)^{\rho-1} \left[ \frac{\rho}{h_t^{\rho}} + (1-\theta)(1-\alpha-\rho) \frac{1}{h_t^{2\rho}} (e_t^M h_t^M)^{\rho} \right]$$

### 5.5.5 Closure

The monetary authority adopts an augmented Taylor rule with nominal interest rate smoothing according to parameter $\rho_r$ and responds to deviations from target inflation and output growth. The term $\varepsilon_t^r$ captures an i.i.d monetary policy shock.

$$r_t = r_{t-1}^{\rho_r} \left[ r \left( \frac{\pi_t}{\pi} \right)^{\omega_\pi} \left( \frac{y_t}{y_{t-1}} \right)^{\omega_y} \right]^{1-\rho_r} \varepsilon_t^r$$

$$\varepsilon_t^r \sim N\left(0, \sigma_r^2\right)$$

The resource constraint states that output may be used for consumption or investment or to cover for adjustment costs to wages and employment (deadweight losses):

$$c_t + i_t = y_t - \sum_i ACw_t^i w_t^i h_t^i e_t^i - \sum_i ACe_t^i$$

## 5.6 Model Dynamics

### 5.6.1 Calibration

We calibrate the model similar to Abbritti and Fahr (2011) and Doepke et al. (2007). The parameter values and description are summarized in Table E.19. The quarterly discount factor $\beta$ is 0.992, yielding an annual rate of 0.97.

The labor market parameters governing the search and matching process are calibrated to match steady state values. The matching function elasticity parameter $\zeta$ is set to 0.5 as in Abbritti and Fahr (2013). The separation rate is set to match a steady state job-finding rate of 0.35 and unemployment rate of 0.08 for males. Given these two values, we than obtain the separation rate of 0.041, which we assume is the same for both genders. Given the separation rate and job filling rate of 0.9, we can obtain the matching efficiency parameter $\overline{m}$ which yields 0.561.

The parameters relating to fertility are calibrated to match empirical facts such as average fertility rates, female time spent with kids, and costs of raising children. The rate at which children reach adulthood $\delta_n$ is 0.025, implying 10 years of child-related utility and costs. The function describing the time cost of children has level parameter $\phi_l$ of 0.088, corresponding to an average fertility rate of 2 kids per family, 3 daily hours allocated by females to care for their children[22], and a curvature parameter $\psi_l$ of 0.5. The parameter describing expenditures per child $\phi_c$ at 0.075 corresponds to 15% of parental net income in steady state, in line with OECD countries such as Norway and Canada.[23] The parameter describing the preference for children in the utility function $\sigma_n$ is 0.398, consistent with an average fertility rate of 2 kids per household.

Parameters governing the supply of labor are calibrated to match gender-specific unemployment and hours worked. Male disutility of labor parameter

[22]We assume female working hours to be 66% of their male counterparts. This is consistent with U.S. Time Use data for years 2005-2013, in which fathers in full-time employment work 6 daily hours compared to an average of 4 hours for mothers in either full or part-time employment. We implicitly assume that childcare is an imperfect substitute for females and that a trade-off exists between working and having children in women's time endowment.

[23]The average annual cost of raising children was estimated at 18% of household income for Norway in 2014 (source: SIFO) and for Canada in 2011 (source: Fraser Institute).

$\sigma_l^M$ is set at 102.4, corresponding to 8 daily working hours and an unemployment rate of 7%. Female disutility of labor parameter $\sigma_l^F$ is set at 475.5, corresponding to 5.3 daily working hours and an unemployment rate of 8%. The Frisch elasticity of labor supply $\xi$ is set at 4.0 as in Trigari (2009) and Christoffel et al. (2009).

Capital has a share $\alpha$ of 0.3 in the firm production function and depreciates at rate $\delta$ of 3%. The elasticity of substitution parameter between females and males in production $\rho$ is 0.65 as in Doepke et al. (2007). Firms have a relative preference for males over females given by $\theta$ at 0.44, which corresponds to a 12% gender wage gap (lower than the 16% average for OECD countries over 2000-13). Workers' bargaining power is higher for males $\eta_M$ at 0.5 than for females $\eta_F$ at 0.35. Firm vacancy posting costs help calibrate the job-finding and job-filling rates, suggesting $\kappa$ at 0.566 implying total vacancy posting costs amount to 3.5% of GDP.

Wage and employment adjustment costs are 0 in the baseline. In the UR setup, we set $\chi_e$ at 1.25 and $\psi_e$ at 1,700 making it more costly to lay-off workers than to fire them. In the RWR setup, we set $\chi_w$ at 36.6 and $\psi_w$ at 24,100 making wages downward rigid. Wages are not indexed against inflation such that $\nu$ is 0. These parameter values are taken directly from Abbritti and Fahr (2013) in which they are calibrated to match the volatility and skewness of wage inflation and employment.

The Taylor rule places a weight $\omega_\pi$ of 1.5 on inflation and $\omega_y$ of 0 on output growth, with interest rate persistence $\rho_r$ of 0.85. The monetary policy shock has 0 persistence and standard deviation $\sigma_r$ of 0.001. The technology shock has persistence $\rho_z$ of 0.95 and standard deviation $\sigma_z$ of 0.0064. These values are the same as Abbritti and Fahr (2013).

### 5.6.2 Impulse Responses under Wage Adjustment Costs

Figures E.6 and E.7 display impulse responses to a one-standard deviation positive and negative monetary policy shock. In response to a contractionary monetary policy shock, firms would like to cut wages and employment. In a setting with downward wage rigidities ($\chi_w$ at 36.6 and $\psi_w$ at 24,100), wages are cut less than the fall in prices, leading to an increase in real wages. This aggravates the contraction of the business cycle with a steep rise in the unemployment rate and large fall in consumption and output. This amplification effect is mirrored in household fertility decisions. Downward wage rigidities lead to asymmetric responses of fertility, with moderate increases in booms and large drops in births during recessions.

Wage adjustment costs in steady state are zero by construction and are not affected by the wage rigidity parameters. By contrast, the stochastic steady state, which considers a large number of simulated shocks, leads to lower fertility compared to the deterministic steady state. In other words, wage rigidities in the presence of economic shocks, reduce average fertility rates, consistent with our empirical findings.

Figure E.8 displays impulse responses to a positive and negative technology shock. Here, the presence of wage adjustment costs play less of a role as real wages are procyclical and result in lower real distortions. Also in this case fertility is procyclical and wage rigidities amplify real effects and the fertility response, with the exception of real wages.

Note that this is a representative agent model, and that allowing for heterogeneity in the form of employed versus unemployed agents would be expected to amplify the mechanisms proposed, with a stronger negative effect of employment volatility, and hence wage adjustment costs, on fertility.

### 5.6.3 Impulse Responses under Employment Adjustment Costs

Figures E.9 and E.10 display impulse responses to a one-standard deviation positive and negative monetary policy shock. As in the previous case, in response to a contractionary monetary policy shock, firms would like to cut wages and employment. In a setting with downward employment rigidities ($\chi_e$ at 50 and $\psi_e$ at 1700), employment can be adjusted less and firms reduce nominal wages to compensate the fall in prices. The overall effect is that nominal wages fall less than prices, so real wages rise. Therefore, employment rigidities dampen the real effects of business cycles on output, consumption and employment but not on real wages. On the other hand, the effect of downward employment rigidities on fertility decisions seems negligible and the response is not significantly asymmetric. Under our preliminary calibration the effect of wage volatility prevails over employment volatility in driving expected wage volatility.

Figure E.11 displays impulse responses to a positive and negative technology shock. Employment rigidities dampen unemployment but amplify the fertility response. On the other hand there is no effect on consumption, output and investment. In this case, the response of the expected wage is in line with our expectations and empirical findings.

## 5.7 Conclusion

This paper investigates the role of labor market institutions that do not explicitly target maternity, in explaining household fertility decisions. We use a panel dataset for 20 OECD countries spanning 1961-2014 including 11 different labor market institutions and estimate panel regressions for the effect of these institutions on total fertility rates. We analyze the roles played by different categories of LMIs, dividing them into employment rigidities (ER) versus real wage rigidities (RWR). This differentiation is important since the former is expected to reduce the volatility of unemployment, whereas the latter reduces the volatility of wages but increases the volatility of unemployment. Since fertility decisions are affected by the possibility of large income shocks, the volatility of unemployment and wages can play a crucial part.

We estimate panel regressions controlling for country and time fixed effects and features such as maternity benefits, economic conditions, and gender inequality. We find that employment rigidities such as employment protection legislation and union strength[24] tend to increase fertility. On the other hand, real wage rigidities such as wage bargaining centralization and unemployment benefits tend to decrease fertility.

We study a mechanism that links LMIs and fertility through the volatility of unemployment and expected wages. We find that unemployment and expected wage volatility is associated with lower fertility. We also find that employment rigidities such as EPL, reduce the volatility of employment and expected wages, whereas wage rigidities such as centralized wage bargaining centralization and unemployment benefits, increase these volatilities. Results using two-stage least squares regressions show that instrumenting the volatility of expected wages and unemployment by these LMIs, we find a negative correlation with fertility, confirming our previous results. We remain cautious in interpreting this as proving the role of unemployment volatility but rather simply *not excluding* this channel.

[24]Whereas a priori we remain agnostic about the predominance of union bargaining over wages versus manning ratios, our empirical findings suggest the latter dominates in our data.

We then build a DSGE model in which we incorporate household fertility decisions as in Lagerborg (2016) and a large set of labor market frictions as in Abbritti and Fahr (2013). We examine the role of Rotemberg-type wage and employment adjustment costs with an asymmetric component that generates downward wage and employment rigidities. Downward wage rigidities amplify real contractions in response to negative demand shocks and lead to large drops in employment and fertility. As a result of this amplification effect, in the presence of demand shocks, downward wage rigidities also reduce the stochastic steady state for fertility. Downward employment rigidities instead, in response to negative demand shocks, tend to dampen the real effects of business-cycles, with the exception of real wages. Indeed nominal wages fall less than prices, so real wages rise. On the other hand, the effect on fertility decisions seems to be negligible.

For further research we could explore the role of price adjustment costs and occasionally binding constraints in increasing the responsiveness of expected wages to unemployment. The former could improve the dynamics for real wages and the latter could capture the irreversibly nature of fertility decision. We could also consider a model with heterogeneous agents - employed versus unemployed. Incorporating unemployment risk would give rise to a precautionary savings motive that could amplify the contractionary effects of negative shocks on the real economy and on fertility, making the role of unemployment volatility extra important in household decicions.

This link we identify between labor market rigidities and fertility has relevant policy implications. For instance, decentralization of wage bargaining could be an alternative to family-targeted policies. Lowering employment protection could dampen the effects of policies that favor fertility. To the extent that labor market reforms affect business cycle volatility, and especially the volatility of unemployment, this may also play a role in household fertility decisions.

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# Appendix A

# Appendix: Confidence and Local Activity: An IV Approach

## A.1 Data description

Figure A.1: Histogram for Sentiment

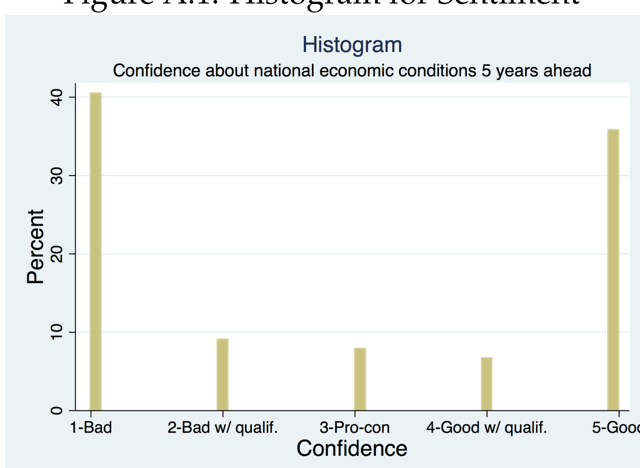


Figure A.2: Histograms for Consumer Buying Attitudes and Personal Finances

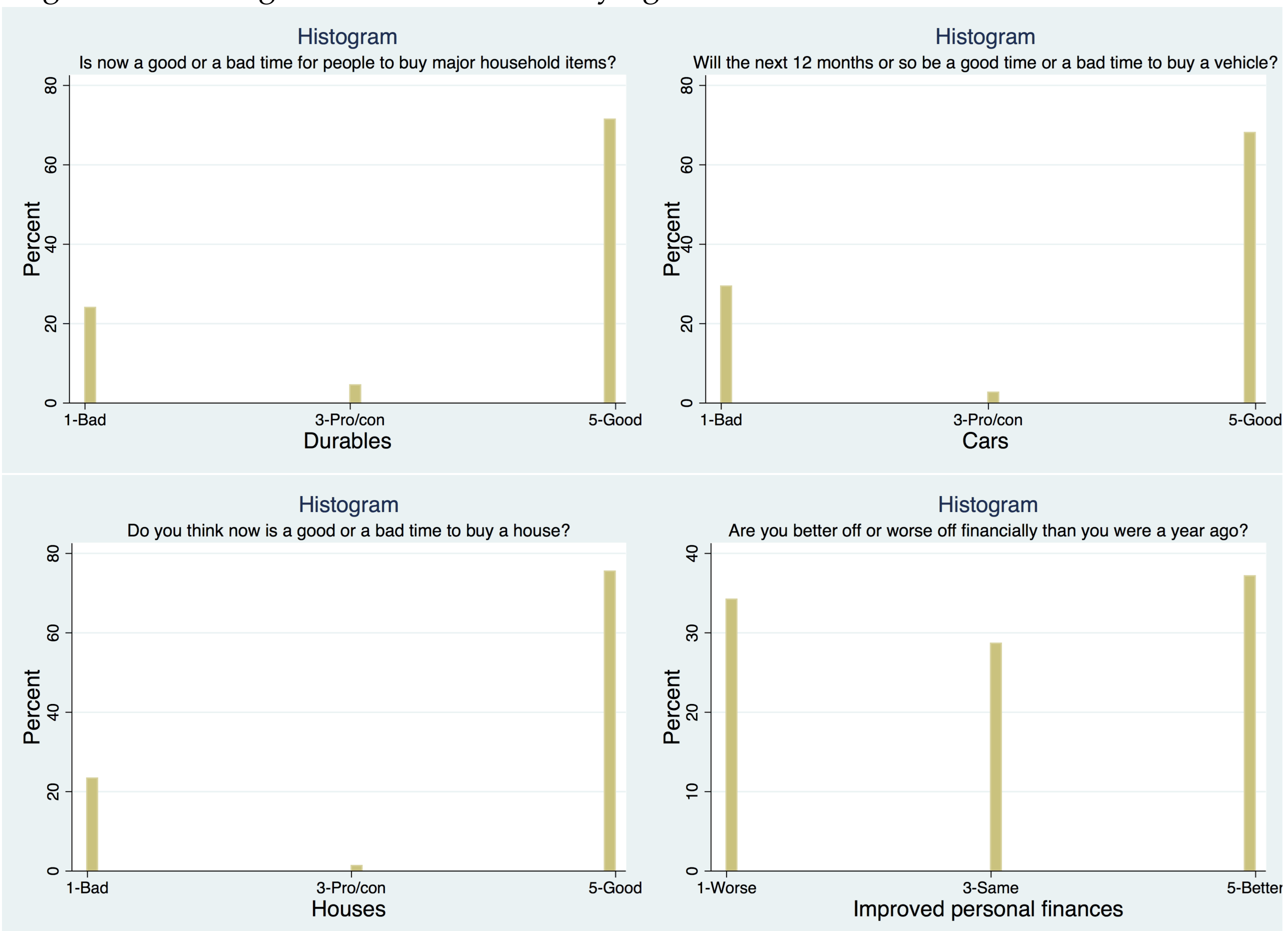


Table A.1: Individual Confidence - Determinants

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | Buying attitudes | | |
| | Confidence | Durables | Cars | Houses |
| Female | -0.293*** | -0.177*** | -0.129*** | -0.101*** |
| | (0.025) | (0.017) | (0.019) | (0.019) |
| Age | -0.306*** | -0.026 | -0.087* | 0.111** |
| | (0.038) | (0.037) | (0.045) | (0.043) |
| Age-squared | 0.029*** | 0.005 | 0.013*** | -0.008* |
| | (0.004) | (0.003) | (0.004) | (0.004) |
| Education | 0.086*** | 0.019* | 0.072*** | 0.119*** |
| | (0.009) | (0.011) | (0.008) | (0.010) |
| Income quintile | 0.075*** | 0.049*** | 0.114*** | 0.131*** |
| | (0.010) | (0.008) | (0.010) | (0.011) |
| Improved personal finances | 0.208*** | 0.124*** | 0.105*** | 0.077*** |
| | (0.006) | (0.005) | (0.006) | (0.008) |
| County unemployment rate | -0.015** | 0.001 | -0.011 | 0.006 |
| | (0.007) | (0.009) | (0.008) | (0.016) |
| Constant | 3.432*** | 3.892*** | 2.952*** | 2.139*** |
| | (0.164) | (0.148) | (0.195) | (0.247) |
| Observations | 35,372 | 35,212 | 35,192 | 36,111 |
| R-squared | 0.124 | 0.087 | 0.076 | 0.091 |
| Time FE | Yes | Yes | Yes | Yes |
| Location FE | MSA | MSA | MSA | MSA |
| SE cluster | state | state | state | state |

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure A.3: U.S. Confidence and Unemployment Rates

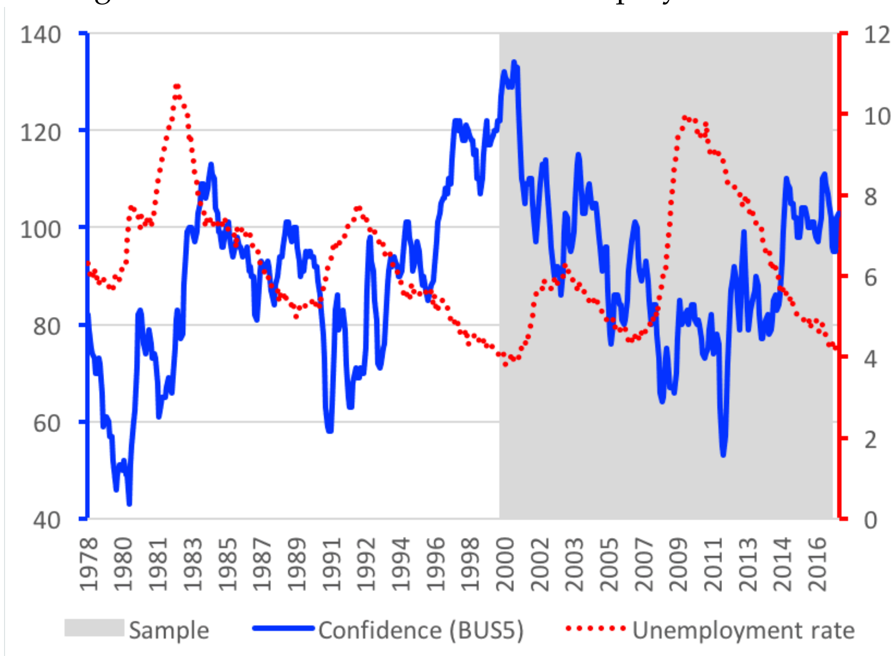


Table A.2: Correlation Coefficients and Summary Statistics

| | BUS5 | BEXP | ICE | ICS | ICC | YTL5 | PAGO | DUR | CAR | HOM | UR |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **CORRELATION COEFFICIENTS** | | | | | | | | | | | |
| Baseline confidence (BUS5) | 1 | | | | | | | | | | |
| **Other confidence measures** | | | | | | | | | | | |
| Confidence (BEXP) | 0.4752 | 1 | | | | | | | | | |
| Confidence (ICE) | 0.8201 | 0.5748 | 1 | | | | | | | | |
| Confidence (ICS) | 0.7296 | 0.5055 | 0.8995 | 1 | | | | | | | |
| Confidence (ICC) | 0.2972 | 0.1959 | 0.3831 | 0.7483 | 1 | | | | | | |
| **Household income** | | | | | | | | | | | |
| Income quintile (YTL5) | 0.1389 | 0.0697 | 0.1387 | 0.1800 | 0.1700 | 1 | | | | | |
| Personal finance (PAGO) | 0.2535 | 0.1510 | 0.3391 | 0.6078 | 0.7700 | 0.1913 | 1 | | | | |
| **Consumer buying attitudes** | | | | | | | | | | | |
| Durables (DUR) | 0.2052 | 0.1502 | 0.2518 | 0.5449 | 0.7695 | 0.0718 | 0.1891 | 1 | | | |
| Cars (CAR) | 0.1992 | 0.1799 | 0.2278 | 0.3035 | 0.2958 | 0.1239 | 0.1357 | 0.3193 | 1 | | |
| Houses (HOM) | 0.1811 | 0.1721 | 0.2010 | 0.2327 | 0.1869 | 0.1715 | 0.1130 | 0.1742 | 0.2362 | 1 | |
| County unemployment rate (UR) | -0.1346 | 0.0008 | -0.1688 | -0.2223 | -0.2137 | -0.1119 | -0.1856 | -0.1460 | -0.0700 | -0.0114 | 1 |
| **SUMMARY STATISTICS** | | | | | | | | | | | |
| Mean | 2.846 | 3.141 | 75.06 | 82.92 | 95.16 | 3.075 | 3.034 | 3.934 | 3.749 | 4.041 | 6.285 |
| Standard deviation | 1.661 | 1.301 | 43.59 | 37.05 | 45.47 | 1.279 | 1.562 | 1.597 | 1.697 | 1.572 | 2.786 |
| Minimum | 1 | 1 | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 1 | -4.2 |
| Maximum | 5 | 5 | 148 | 150 | 153 | 5 | 5 | 5 | 5 | 5 | 30.4 |
| No. observations | 69,140 | 70,262 | 71,366 | 71,366 | 71,366 | 67,277 | 71,254 | 68,841 | 68,869 | 70,345 | 659,370 |

Figure A.4: Distribution of School Shootings over Time

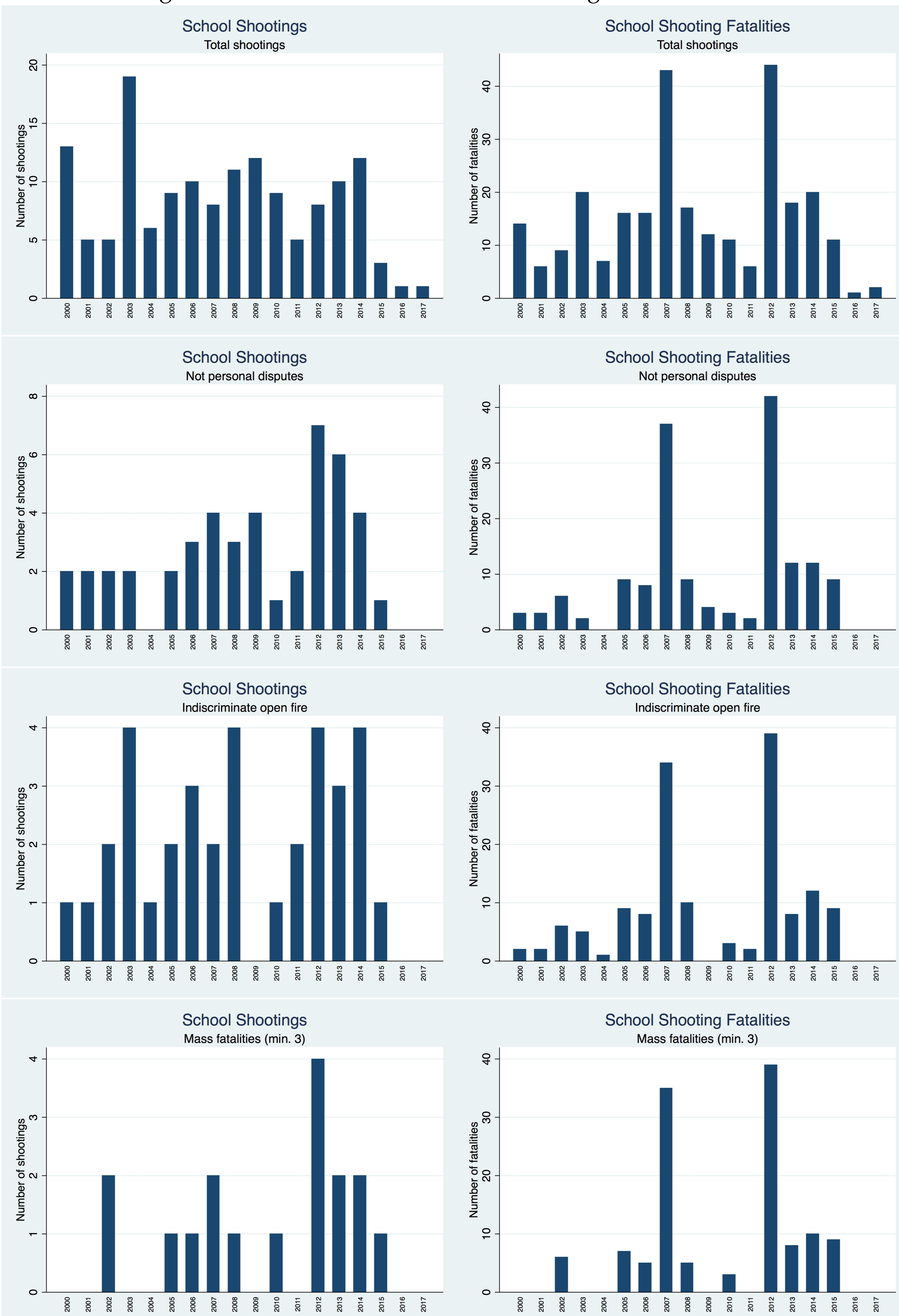


Figure A.6: Histogram of Mass Shooting Fatalities

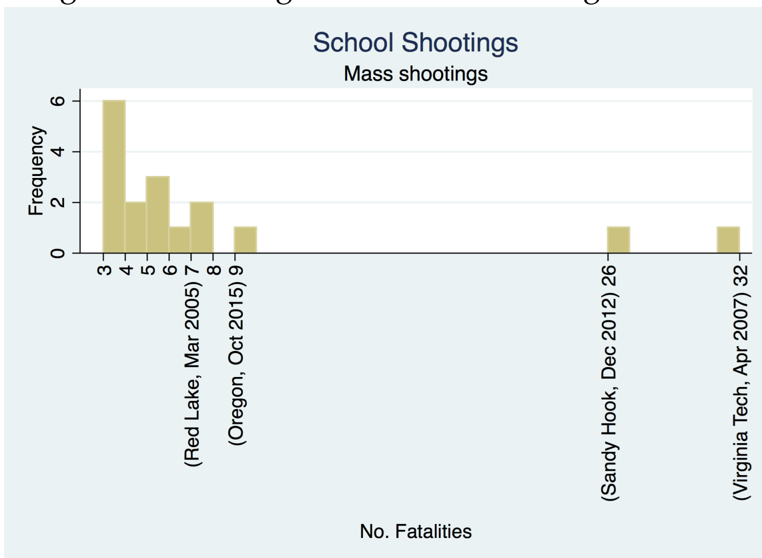



Figure A.7: Frequency of School Shootings by State

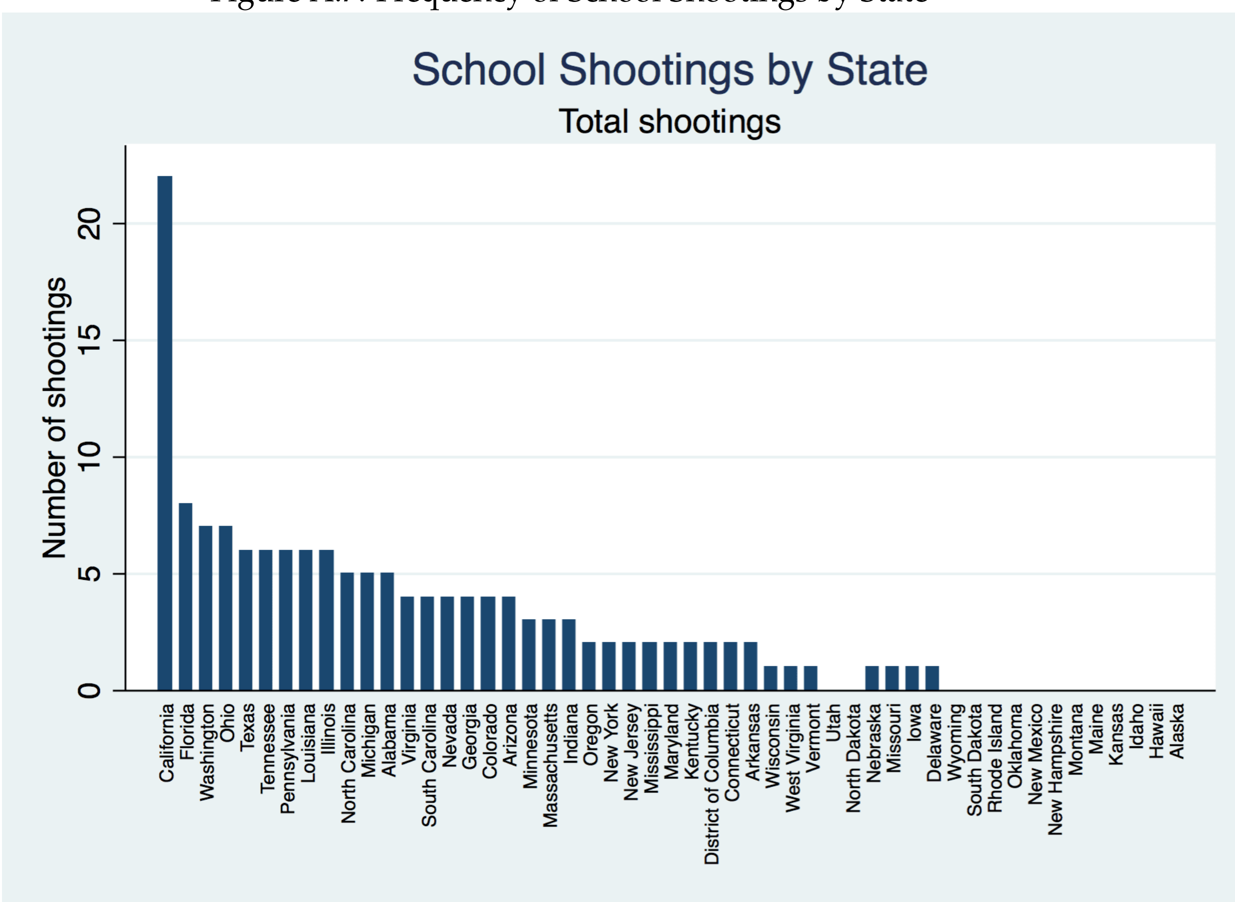


Figure A.5: Cross-Sectional Distribution of School Shooting Fatalities

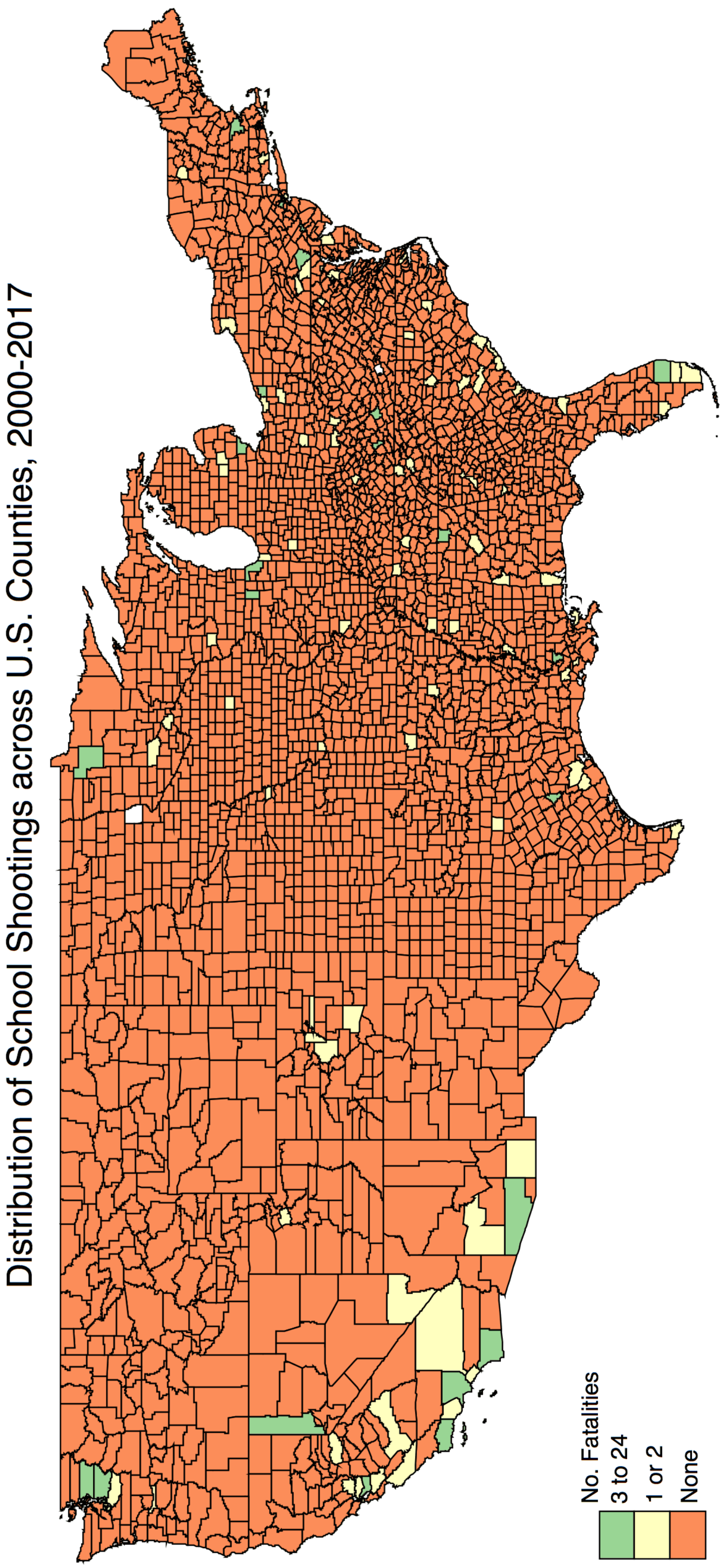


Table A.3: Exogeneity of Shootings: T-test for Difference in Means

| Mean value for: | Counties without Shootings | Counties with Shootings | T-statistic |
|---|---|---|---|
| Confidence | 2.74 | 2.91 | 1.61* |
| Δ Confidence | 0.02 | 0.06 | 0.39 |
| Unemployment rate | 6.50 | 6.35 | -0.61 |
| Δ Unemployment rate x 100 | 0.10 | 0.17 | 1.13 |

Table A.4: Correlation Coefficients: Shootings and Local Economic Conditions

| | Confidence | ICS | ICC | ICE | Δ Confidence | ΔICS | ΔICC | ΔICE |
|---|---|---|---|---|---|---|---|---|
| Shootings - Total | 0.0076 | 0.0074 | 0.0045 | 0.0073 | 0.0143 | 0.0124 | 0.0102 | 0.0088 |
| Shootings - Not personal | 0.0070 | 0.0062 | 0.0042 | 0.0058 | 0.0145 | 0.0111 | 0.0089 | 0.0080 |
| Shootings - Open fire | 0.0065 | 0.0055 | 0.0036 | 0.0052 | 0.0137 | 0.0101 | 0.0074 | 0.0074 |
| Shootings - Mass | 0.0072 | 0.0066 | 0.0043 | 0.0063 | 0.0135 | 0.0116 | 0.0083 | 0.0083 |

Table A.5: Exogeneity of Shootings: Placebo Test

| | (1)<br>Δ Confidence | (2)<br>Δ Confidence | (3)<br>Shootings (+6) | (4)<br>Δ Confidence | (5)<br>Δ Confidence | (6)<br>Shootings (+6) |
|---|---|---|---|---|---|---|
| Total shootings | -0.052*** | | | -0.043*** | | |
| | (0.017) | | | (0.014) | | |
| Total shootings (+6) | | -0.017 | | | -0.006 | |
| | | (0.020) | | | (0.018) | |
| Δ Confidence | | | -0.002 | | | -0.001 |
| | | | (0.002) | | | (0.002) |
| Constant | 0.246 | 0.246 | 0.126 | 0.265 | 0.264 | 0.126* |
| | (0.225) | (0.224) | (0.103) | (0.226) | (0.225) | (0.075) |
| Observations | 31,061 | 31,061 | 31,061 | 31,061 | 31,061 | 31,061 |
| R-squared | 0.043 | 0.042 | 0.049 | 0.043 | 0.043 | 0.052 |
| Time FE | YES | YES | YES | YES | YES | YES |
| Location FE | | | | County | County | County |
| SE cluster | County | County | County | County | County | County |
| No. counties | | | | 2,622 | 2,622 | 2,622 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.6: Exogeneity of Shootings: Linear Probability Model

| | (1) | (2) |
|---|---|---|
| Counties in sample | $\geq$ 1 shooting | All counties |
| | P(shooting) | P(shooting) |
| Unemployment rate (-1) | 0.019 | 0.4e-3 |
| | (0.056) | (1.5e-3) |
| Constant | 0.008 | 0.000 |
| | (0.008) | (0.000) |
| Observations | 23,310 | 659,370 |
| R-squared | 0.013 | 0.000 |
| No. counties | 111 | 3,144 |
| Time FE | YES | YES |
| Location FE | County | County |
| SE cluster | state | state |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

## A.2 Individual level Results

Table A.7: IV First Stage (Individual level)

| | (1)<br>Δ Confidence | (2)<br>Δ Confidence | (3)<br>Δ Confidence | (4)<br>Δ Confidence |
|---|---|---|---|---|
| Total shootings | -0.033*** | | | |
| | (0.011) | | | |
| Not personal disputes | | -0.036*** | | |
| | | (0.009) | | |
| Indiscriminate open fire | | | -0.045*** | |
| | | | (0.010) | |
| Mass fatalities | | | | -0.039*** |
| | | | | (0.007) |
| Δ Improved personal finances | 0.059*** | 0.059*** | 0.059*** | 0.059*** |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| Δ County unemployment rate | -0.020 | -0.020 | -0.020 | -0.020 |
| | (0.019) | (0.019) | (0.019) | (0.019) |
| Constant | -0.026 | -0.027 | -0.027 | -0.027 |
| | (0.135) | (0.135) | (0.135) | (0.135) |
| Observations | 35,318 | 35,318 | 35,318 | 35,318 |
| R-squared | 0.041 | 0.041 | 0.041 | 0.041 |
| Time FE | Yes | Yes | Yes | Yes |
| Location FE | MSA | MSA | MSA | MSA |
| SE cluster | MSA | MSA | MSA | MSA |
| Weak instrument test | | | | |
| F-statistic | 9.931 | 16.21 | 20.54 | 32.96 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.8: IV Second Stage: Durables Buying Appetite (Individual level)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Shootings IV: | Total | Not pers. | Open fire | Mass |
| | Δ Durables | Δ Durables | Δ Durables | Δ Durables |
| Δ Confidence | 0.681 | 0.829** | 0.707** | 1.041*** |
| | (0.595) | (0.418) | (0.362) | (0.242) |
| Δ Improved personal finances | 0.009 | -0.001 | 0.007 | -0.013 |
| | (0.039) | (0.027) | (0.024) | (0.019) |
| Δ County unemployment rate | 0.012 | 0.016 | 0.013 | 0.021 |
| | (0.023) | (0.023) | (0.021) | (0.023) |
| Constant | 0.362 | 0.350** | 0.360** | 0.331* |
| | (0.170) | (0.179) | (0.163) | (0.196) |
| Observations | 31,624 | 31,624 | 31,624 | 31,624 |
| Time FE | Yes | Yes | Yes | Yes |
| Location FE | MSA | MSA | MSA | MSA |
| SE cluster | MSA | MSA | MSA | MSA |

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.9: IV Second Stage: Car Buying Appetite (Individual level)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Shootings IV: | Total | Not pers. | Open fire | Mass |
| | Δ Cars | Δ Cars | Δ Cars | Δ Cars |
| Δ Confidence | -0.854 | -1.662 | -1.278 | -1.483 |
| | (1.414) | (1.799) | (1.155) | (1.389) |
| Δ Improved personal finances | 0.075 | 0.123 | 0.100 | 0.112 |
| | (0.084) | (0.106) | (0.069) | (0.082) |
| Δ County unemployment rate | -0.018 | -0.031 | -0.025 | -0.029 |
| | (0.037) | (0.050) | (0.039) | (0.044) |
| Constant | -0.098 | -0.079 | -0.088 | -0.083 |
| | (0.216) | (0.303) | (0.259) | (0.282) |
| Observations | 32,695 | 32,695 | 32,695 | 32,695 |
| Time FE | Yes | Yes | Yes | Yes |
| Location FE | MSA | MSA | MSA | MSA |
| SE cluster | MSA | MSA | MSA | MSA |

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.10: IV Second Stage: House Buying Appetite (Individual level)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Shootings IV: | Total | Not pers. | Open fire | Mass |
| | Δ Houses | Δ Houses | Δ Houses | Δ Houses |
| Δ Confidence | -1.028 | -0.667 | -0.692 | -0.525 |
| | (1.006) | (0.680) | (0.565) | (0.547) |
| Δ Improved personal finances | 0.087 | 0.066 | 0.067* | 0.057* |
| | (0.061) | (0.041) | (0.035) | (0.033) |
| Δ County unemployment rate | -0.026 | -0.019 | -0.019 | -0.016 |
| | (0.034) | (0.026) | (0.025) | (0.024) |
| Constant | -0.637*** | -0.615*** | -0.616*** | -0.606*** |
| | (0.227) | (0.188) | (0.187) | (0.176) |
| Observations | 34,296 | 34,296 | 34,296 | 34,296 |
| Time FE | Yes | Yes | Yes | Yes |
| Location FE | MSA | MSA | MSA | MSA |
| SE cluster | MSA | MSA | MSA | MSA |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.11: OLS Regression (Individual level)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Δ Durables | Δ Cars | Δ Houses | Δ Durables | Δ Cars | Δ Houses |
| Δ Confidence | 0.061*** | 0.053*** | 0.034*** | 0.058*** | 0.053*** | 0.034*** |
| | (0.006) | (0.007) | (0.006) | (0.006) | (0.007) | (0.006) |
| Δ Improved personal finances | | | | 0.047*** | 0.022*** | 0.024*** |
| | | | | (0.007) | (0.009) | (0.006) |
| Δ County unemployment rate | | | | -0.004 | -0.004 | -0.005 |
| | | | | (0.017) | (0.022) | (0.019) |
| Constant | -0.051 | 0.000 | -0.474*** | 0.416*** | -0.120 | -0.571*** |
| | (0.123) | (0.172) | (0.157) | (0.130) | (0.183) | (0.157) |
| Observations | 32,695 | 32,768 | 34,379 | 32,624 | 32,695 | 34,296 |
| R-squared | 0.022 | 0.018 | 0.018 | 0.038 | 0.034 | 0.034 |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Location FE | No | No | No | MSA | MSA | MSA |
| SE cluster | MSA | MSA | MSA | MSA | MSA | MSA |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## A.3 County level Results

Table A.12: IV First Stage (County level)

| | (1)<br>Δ Confidence | (2)<br>Δ Confidence | (3)<br>Δ Confidence | (4)<br>Δ Confidence |
|---|---|---|---|---|
| Total shootings | -0.058*** | | | |
| | (0.017) | | | |
| Not personal disputes | | -0.050*** | | |
| | | (0.016) | | |
| Indiscriminate open fire | | | -0.057*** | |
| | | | (0.015) | |
| Mass fatalities ($\geq 3$) | | | | -0.057*** |
| | | | | (0.012) |
| <u>Controls:</u> | | | | |
| Δ Improved personal finances | 0.046*** | 0.046*** | 0.046*** | 0.046*** |
| | (0.011) | (0.011) | (0.011) | (0.011) |
| Constant | -0.667*** | -0.663*** | -0.669*** | -0.669*** |
| | (0.243) | (0.242) | (0.242) | (0.242) |
| Time FE, MSA FE, MSA trend | Yes | Yes | Yes | Yes |
| 12 lags of unemployment | Yes | Yes | Yes | Yes |
| Observations | 30,113 | 30,113 | 30,113 | 30,113 |
| R-squared | 0.063 | 0.063 | 0.063 | 0.063 |
| SE cluster | State | State | State | State |
| Weak instrument test | | | | |
| F-statistic | 11.23 | 9.744 | 14.27 | 22.52 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure A.8: IV Unemployment Response to a Negative Confidence Shock

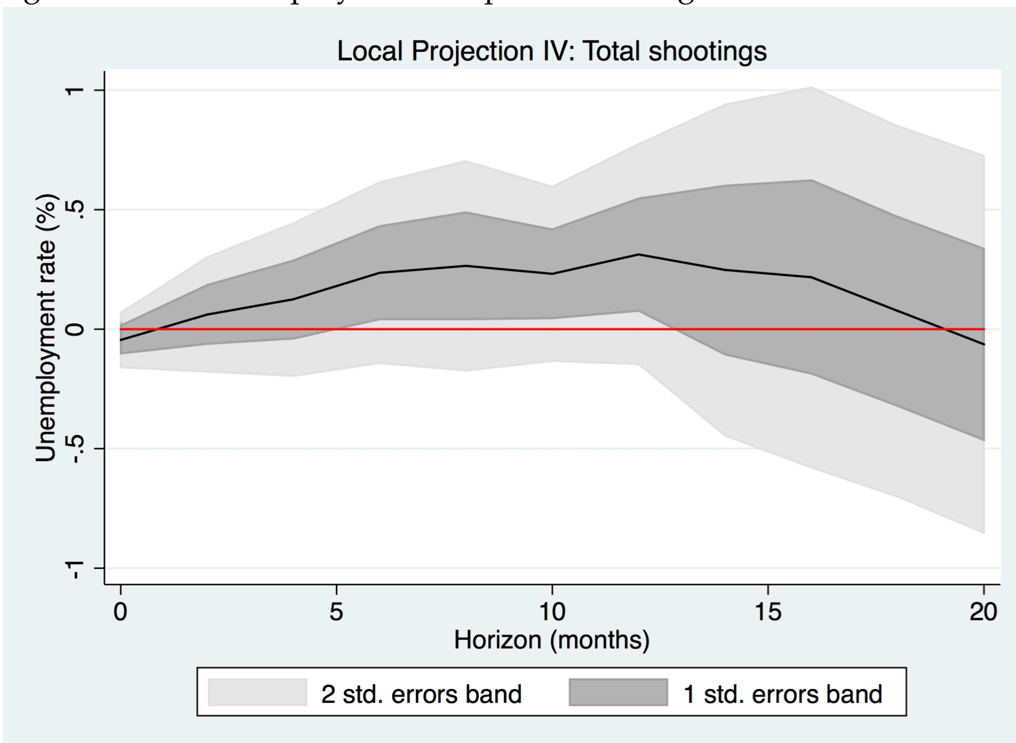



Figure A.9: IV Unemployment Response to a Negative Confidence Shock

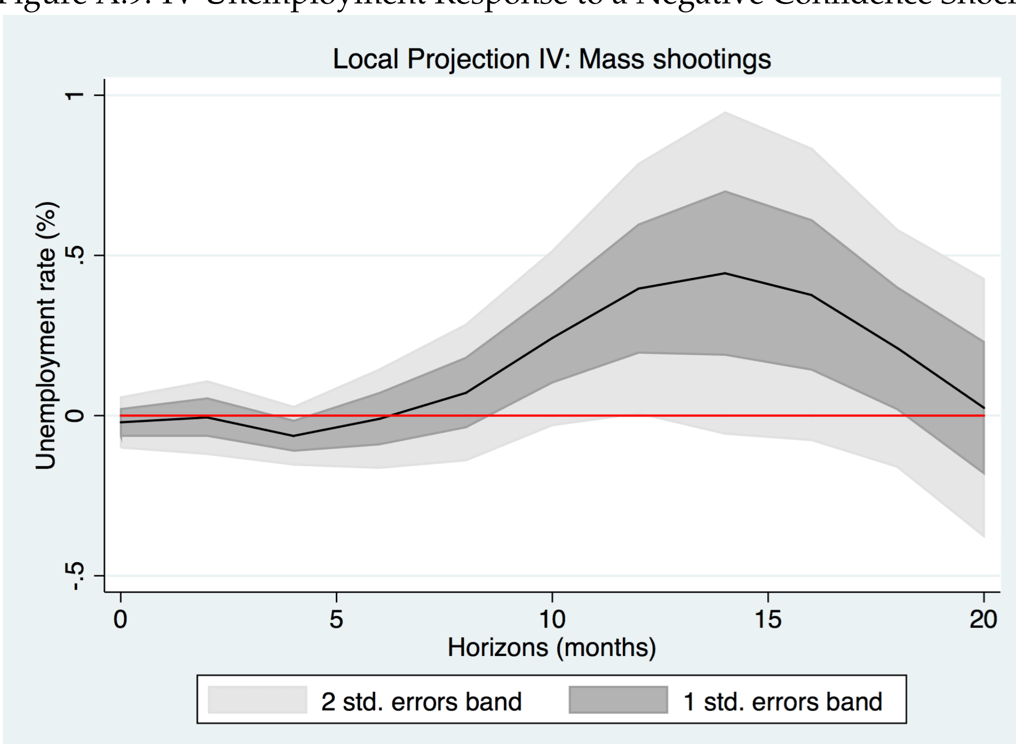
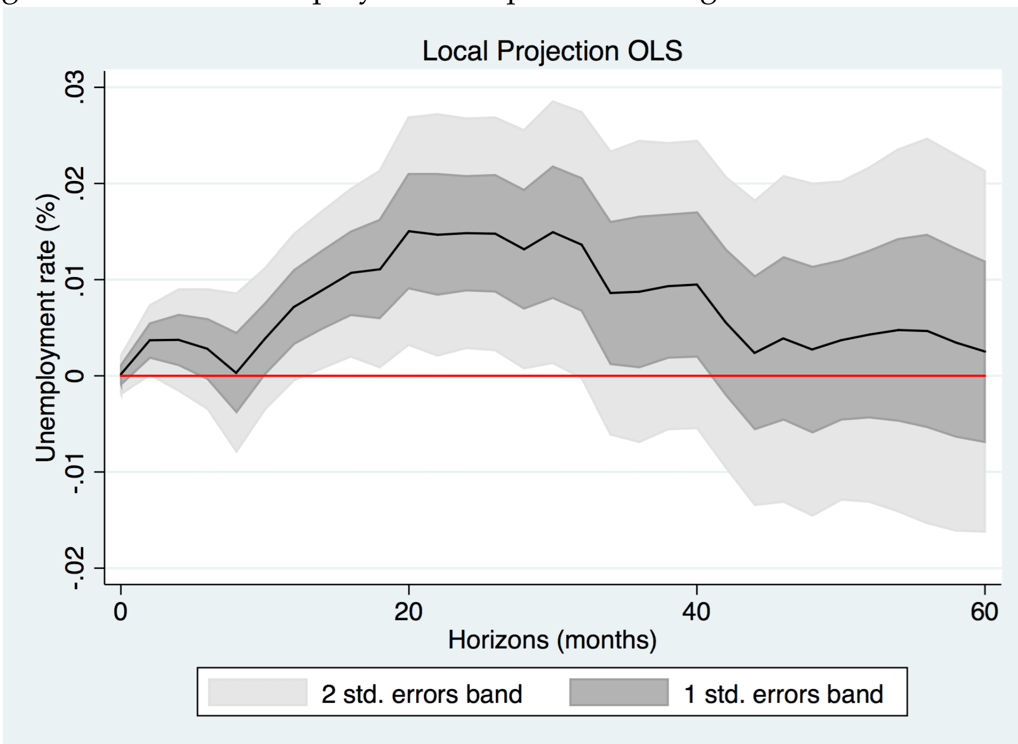


Figure A.10: OLS Unemployment Response to a Negative Confidence Shock



## A.4 Robustness

Table A.13: Robustness to Initial Conditions, Clustering, and Weights (Individual level)

| | (1)<br>Δ Confidence | (2)<br>Δ Confidence | (3)<br>Δ Confidence | (4)<br>Δ Confidence |
|---|---|---|---|---|
| Total shootings | -0.034*** | | | |
| | (0.010) | | | |
| Not personal disputes | | -0.031*** | | |
| | | (0.010) | | |
| Indiscrim. open fire | | | -0.036*** | |
| | | | (0.011) | |
| Mass fatalities ($\geq 3$) | | | | -0.034*** |
| | | | | (0.010) |
| Δ Improved personal finances | 0.137*** | 0.137*** | 0.137*** | 0.137*** |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Δ County unemployment rate | -0.008 | -0.008 | -0.008 | -0.008 |
| | (0.013) | (0.013) | (0.013) | (0.013) |
| Initial confidence | -0.593*** | -0.593*** | -0.593*** | -0.593*** |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Initial personal finances | 0.178*** | 0.178*** | 0.178*** | 0.178*** |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Constant | 1.606*** | 1.606*** | 1.606*** | 1.606*** |
| | (0.104) | (0.104) | (0.104) | (0.104) |
| Observations | 36,276 | 36,276 | 36,276 | 36,276 |
| R-squared | 0.322 | 0.322 | 0.322 | 0.322 |
| Time FE | Yes | Yes | Yes | Yes |
| Location FE | MSA | MSA | MSA | MSA |
| SE cluster | State | State | State | State |
| Weak instrument test | | | | |
| F-statistic | 12.42 | 9.688 | 10.57 | 11.21 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.14: Robustness to Initial Conditions, Fixed Effects, Trends, and Clustering (County level)

| | (1)<br>Δ Confidence | (2)<br>Δ Confidence | (3)<br>Δ Confidence | (4)<br>Δ Confidence |
|---|---|---|---|---|
| Total shootings | -0.036*** | | | |
| | (0.009) | | | |
| Not personal disputes | | -0.030*** | | |
| | | (0.008) | | |
| Indiscriminate open fire | | | -0.033*** | |
| | | | (0.008) | |
| Mass fatalities ($\geq 3$) | | | | -0.033*** |
| | | | | (0.007) |
| Δ Improved personal finances | 0.123*** | 0.123*** | 0.123*** | 0.123*** |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| Initial confidence | -0.594*** | -0.594*** | -0.594*** | -0.594*** |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| Initial personal finances | 0.169*** | 0.169*** | 0.169*** | 0.169*** |
| | (0.009) | (0.009) | (0.009) | (0.009) |
| Constant | 1.057*** | 1.057*** | 1.053*** | 1.053*** |
| | (0.216) | (0.216) | (0.215) | (0.215) |
| Observations | 30,113 | 30,113 | 30,113 | 30,113 |
| R-squared | 0.323 | 0.323 | 0.323 | 0.323 |
| No. counties | 2,608 | 2,608 | 2,608 | 2,608 |
| Time FE | Yes | Yes | Yes | Yes |
| Location FE | County | County | County | County |
| SE cluster | MSA | MSA | MSA | MSA |
| Weak instrument test | | | | |
| F-statistic | 15.03 | 13.93 | 16.41 | 20.64 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.15: Robustness to Weighting by No. of County Interviews (County level)

| | (1)<br>Δ Confidence | (2)<br>Δ Confidence | (3)<br>Δ Confidence | (4)<br>Δ Confidence |
|---|---|---|---|---|
| Total shootings | -0.033** | | | |
| | (0.013) | | | |
| Not personal disputes | | -0.025** | | |
| | | (0.012) | | |
| Indiscriminate open fire | | | -0.031*** | |
| | | | (0.011) | |
| Mass shootings | | | | -0.030*** |
| | | | | (0.009) |
| Δ Improved personal finances | 0.134*** | 0.134*** | 0.134*** | 0.134*** |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Initial confidence | -0.590*** | -0.590*** | -0.590*** | -0.590*** |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Initial personal finances | 0.175*** | 0.175*** | 0.175*** | 0.175*** |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| Constant | 1.013*** | 1.015*** | 1.014*** | 1.014*** |
| | (0.169) | (0.168) | (0.168) | (0.168) |
| Observations | 30,151 | 30,151 | 30,151 | 30,151 |
| R-squared | 0.329 | 0.329 | 0.329 | 0.329 |
| Time FE | Yes | Yes | Yes | Yes |
| MSA FE | Yes | Yes | Yes | Yes |
| MSA trend | Yes | Yes | Yes | Yes |
| SE cluster | State | State | State | State |
| Weak instrument test | | | | |
| F-statistic | 6.615 | 4.787 | 8.563 | 10.11 |

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.16: Robustness to Shooting Outliers (County level)

| | (1)<br>Δ Confidence | (2)<br>Δ Confidence | (3)<br>Δ Confidence |
|---|---|---|---|
| Mass shooting dummy | -0.403*** | -0.369*** | -0.184*** |
| | (0.073) | (0.078) | (0.058) |
| Δ Improved personal finances | | 0.048*** | 0.038*** |
| | | (0.009) | (0.007) |
| Δ County unemployment rate | | -0.032 | -0.023 |
| | | (0.029) | (0.028) |
| Initial confidence | | | -0.565*** |
| | | | (0.005) |
| Constant | 0.244 | 0.073 | 2.254*** |
| | (0.201) | (0.220) | (0.177) |
| Observations | 31,061 | 30,976 | 30,976 |
| R-squared | 0.042 | 0.053 | 0.316 |
| Time FE | Yes | Yes | Yes |
| Location FE | No | MSA | MSA |
| SE cluster | State | State | State |
| Weak instrument test | | | |
| F-statistic | 30.92 | 22.18 | 10.23 |

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.17: Robustness to Virginia Tech (Individual level)

| | (1)<br>Δ Confidence | (2)<br>Δ Confidence | (3)<br>Δ Confidence | (4)<br>Δ Confidence |
|---|---|---|---|---|
| Total shootings | -0.033*** | | | |
| | (0.011) | | | |
| Not personal disputes | | -0.036*** | | |
| | | (0.009) | | |
| Indiscriminate open fire | | | -0.045*** | |
| | | | (0.010) | |
| Mass fatalities ($\geq 3$) | | | | -0.039*** |
| | | | | (0.007) |
| Δ Improved personal finances | 0.059*** | 0.059*** | 0.059*** | 0.059*** |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| Δ County unemployment rate | -0.020 | -0.020 | -0.020 | -0.020 |
| | (0.019) | (0.019) | (0.019) | (0.019) |
| Constant | -0.026 | -0.027 | -0.027 | -0.027 |
| | (0.135) | (0.135) | (0.135) | (0.135) |
| Observations | 35,318 | 35,318 | 35,318 | 35,318 |
| R-squared | 0.041 | 0.041 | 0.041 | 0.041 |
| Time FE | Yes | Yes | Yes | Yes |
| Location FE | MSA | MSA | MSA | MSA |
| SE cluster | State | State | State | State |
| Weak instrument test | | | | |
| F-statistic | 9.931 | 16.21 | 20.54 | 32.96 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.18: Robustness to All Interview Responses (County level)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Δ Confidence | Δ Confidence | Δ Confidence | Δ Confidence |
| Total shootings | -0.027** | | | |
| | (0.010) | | | |
| Not personal disputes | | -0.030*** | | |
| | | (0.006) | | |
| Indiscriminate open fire | | | -0.028*** | |
| | | | (0.006) | |
| Mass fatalities ($\geq$ 3) | | | | -0.025*** |
| | | | | (0.003) |
| Confidence (-6) | -0.820*** | -0.820*** | -0.820*** | -0.820*** |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| Δ Improved personal finances | 0.200*** | 0.200*** | 0.200*** | 0.200*** |
| | (0.009) | (0.009) | (0.009) | (0.009) |
| Improved personal finances (-6) | 0.199*** | 0.199*** | 0.199*** | 0.199*** |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| Constant | 1.959*** | 1.960*** | 1.958*** | 1.958*** |
| | (0.164) | (0.164) | (0.163) | (0.163) |
| Observations | 38,789 | 38,789 | 38,789 | 38,789 |
| R-squared | 0.445 | 0.445 | 0.445 | 0.445 |
| Time FE | Yes | Yes | Yes | Yes |
| Location FE | MSA | MSA | MSA | MSA |
| SE cluster | state | state | state | state |
| Weak instrument test | | | | |
| F-statistic | 6.838 | 21.95 | 21.37 | 79.07 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.19: Robustness to BEXP Confidence 1 Year Ahead (County level)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Δ BEXP | Δ BEXP | Δ BEXP | Δ BEXP |
| Total shootings | -0.029*** | | | |
| | (0.008) | | | |
| Not personal disputes | | -0.022** | | |
| | | (0.009) | | |
| Indiscriminate open fire | | | -0.021** | |
| | | | (0.008) | |
| Mass fatalities ($\geq 3$) | | | | -0.024*** |
| | | | | (0.006) |
| Δ Improved personal finances | 0.018** | 0.018** | 0.018** | 0.018** |
| | (0.009) | (0.009) | (0.009) | (0.009) |
| Constant | -0.452*** | -0.451*** | -0.453*** | -0.453*** |
| | (0.154) | (0.154) | (0.153) | (0.153) |
| Observations | 31,294 | 31,294 | 31,294 | 31,294 |
| R-squared | 0.059 | 0.059 | 0.059 | 0.059 |
| Time FE | Yes | Yes | Yes | Yes |
| MSA FE | Yes | Yes | Yes | Yes |
| SE cluster | State | State | State | State |
| Weak instrument test | | | | |
| F-statistic | 13.52 | 5.509 | 7.110 | 18.03 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.20: Robustness to Broad Index of Consumer Sentiment (County level)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Δ ICS | Δ ICS | Δ ICS | Δ ICS |
| Total shootings | -0.208 | | | |
| | (0.211) | | | |
| Not personal disputes | | -0.337** | | |
| | | (0.162) | | |
| Indiscriminate open fire | | | -0.270 | |
| | | | (0.167) | |
| Mass fatalities ($\geq 3$) | | | | -0.442*** |
| | | | | (0.102) |
| Δ Improved personal finances | 8.764*** | 8.764*** | 8.764*** | 8.764*** |
| | (0.172) | (0.172) | (0.172) | (0.172) |
| Constant | -16.022*** | -16.019*** | -16.041*** | -16.065*** |
| | (2.680) | (2.678) | (2.678) | (2.684) |
| Observations | 32,166 | 32,166 | 32,166 | 32,166 |
| R-squared | 0.275 | 0.275 | 0.275 | 0.275 |
| Time FE | Yes | Yes | Yes | Yes |
| MSA FE | Yes | Yes | Yes | Yes |
| SE cluster | State | State | State | State |
| Weak instrument test | | | | |
| F-statistic | 0.976 | 4.312 | 2.595 | 18.92 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.21: Robustness to ICE Confidence (County level)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Δ ICE | Δ ICE | Δ ICE | Δ ICE |
| Total shootings | -0.341 | | | |
| | (0.246) | | | |
| Not personal disputes | | -0.533** | | |
| | | (0.261) | | |
| Indiscriminate open fire | | | -0.399* | |
| | | | (0.208) | |
| Mass fatalities ($\geq 3$) | | | | -0.537*** |
| | | | | (0.141) |
| Δ Improved personal finances | 1.663*** | 1.663*** | 1.663*** | 1.663*** |
| | (0.186) | (0.186) | (0.186) | (0.186) |
| Constant | -27.216*** | -27.209*** | -27.241*** | -27.260*** |
| | (3.853) | (3.851) | (3.856) | (3.868) |
| Observations | 32,166 | 32,166 | 32,166 | 32,166 |
| R-squared | 0.090 | 0.090 | 0.090 | 0.090 |
| Time FE | Yes | Yes | Yes | Yes |
| MSA FE | Yes | Yes | Yes | Yes |
| SE cluster | State | State | State | State |
| Weak instrument test | | | | |
| F-statistic | 1.915 | 4.183 | 3.691 | 14.56 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.22: Robustness to ICC Confidence (County level)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Δ ICC | Δ ICC | Δ ICC | Δ ICC |
| Total shootings | 0.025 | | | |
| | (0.773) | | | |
| Not personal disputes | | -0.207 | | |
| | | (0.679) | | |
| Indiscriminate open fire | | | -0.194 | |
| | | | (0.679) | |
| Mass fatalities ($\geq 3$) | | | | -0.282 |
| | | | | (0.527) |
| Constant | 0.710 | 0.700 | 0.682 | 0.670 |
| | (4.387) | (4.376) | (4.401) | (4.386) |
| Observations | 32,259 | 32,259 | 32,259 | 32,259 |
| R-squared | 0.053 | 0.053 | 0.053 | 0.053 |
| Time FE | Yes | Yes | Yes | Yes |
| MSA FE | Yes | Yes | Yes | Yes |
| SE cluster | State | State | State | State |
| Weak instrument test | | | | |
| F-statistic | 0.00105 | 0.0930 | 0.0817 | 0.286 |

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.23: Robustness to MSA-level Shootings (County level)

| | (1) Δ Confidence | (2) Δ Confidence | (3) Δ Confidence | (4) Δ Confidence |
|---|---|---|---|---|
| MSA-level total shootings | -0.022** | | | |
| | (0.010) | | | |
| MSA-level not personal disputes | | -0.024** | | |
| | | (0.011) | | |
| MSA-level open fire shootings | | | -0.038*** | |
| | | | (0.011) | |
| MSA-level mass shootings | | | | -0.044*** |
| | | | | (0.009) |
| Constant | 0.272 | 0.271 | 0.271 | 0.271 |
| | (0.215) | (0.215) | (0.215) | (0.215) |
| Observations | 24,476 | 24,476 | 24,476 | 24,476 |
| R-squared | 0.044 | 0.044 | 0.044 | 0.044 |
| No. counties | 1,063 | 1,063 | 1,063 | 1,063 |
| Time FE | Yes | Yes | Yes | Yes |
| Location FE | County | County | County | County |
| SE cluster | State | State | State | State |
| Weak instrument test | | | | |
| F-statistic | 4.624 | 4.316 | 12.52 | 25.28 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.24: Robustness to MSA-level Shooting Spillovers (County level)

| | (1) Δ Confidence | (2) Δ Confidence | (3) Δ Confidence | (4) Δ Confidence |
|---|---|---|---|---|
| Total shootings in county | -0.042*** | | | |
| | (0.013) | | | |
| Total shootings in other counties of MSA | 0.016 | | | |
| | (0.021) | | | |
| Impersonal shootings in county | | -0.037*** | | |
| | | (0.013) | | |
| Impersonal shootings in other counties of MSA | | 0.009 | | |
| | | (0.015) | | |
| Open fire shootings in county | | | -0.050*** | |
| | | | (0.015) | |
| Open fire shootings in other counties of MSA | | | -0.008 | |
| | | | (0.014) | |
| Mass shootings in county | | | | -0.050*** |
| | | | | (0.013) |
| Mass shootings in other counties of MSA | | | | -0.032** |
| | | | | (0.015) |
| Constant | 0.272 | 0.271 | 0.271 | 0.271 |
| | (0.215) | (0.215) | (0.215) | (0.215) |
| R-squared | 0.044 | 0.044 | 0.044 | 0.044 |
| Observations | 24,476 | 24,476 | 24,476 | 24,476 |
| No. counties | 1,063 | 1,063 | 1,063 | 1,063 |
| Time FE | Yes | Yes | Yes | Yes |
| Location FE | County | County | County | County |
| SE cluster | State | State | State | State |
| Weak instrument test | | | | |
| F-statistic | 5.424 | 4.430 | 6.200 | 10.61 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.25: Robustness to MSA-level Confidence Spillovers (County level)

| | (1) Δ Confidence | (2) Δ Confidence | (3) Δ Confidence |
|---|---|---|---|
| Δ Confidence in other counties in MSA | -0.004 | -0.004 | -0.004 |
| | (0.008) | (0.008) | (0.008) |
| Mass fatalities in county | | | -0.050*** |
| | | | (0.013) |
| Mass fatalities in other counties in MSA | | -0.031** | -0.032** |
| | | (0.015) | (0.015) |
| Constant | 0.272 | 0.272 | 0.272 |
| | (0.215) | (0.215) | (0.216) |
| R-squared | 0.044 | 0.044 | 0.044 |
| Observations | 24,476 | 24,476 | 24,476 |
| No. counties | 1,063 | 1,063 | 1,063 |
| Time FE | Yes | Yes | Yes |
| Location FE | County | County | County |
| SE cluster | State | State | State |

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure A.11: Robustness of 2$^{nd}$ Stage: Specification (County level)

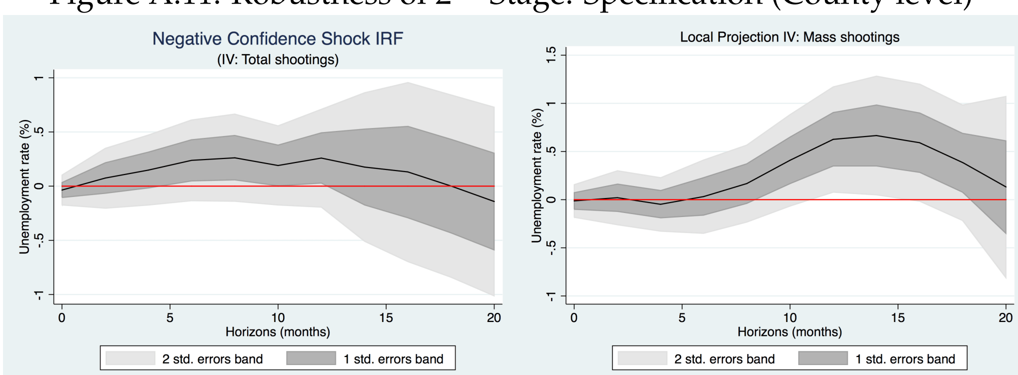


Table A.26: Robustness of Second Stage (Individual level)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Δ Confidence | Δ DUR | Δ Confidence | Δ DUR | Δ Confidence | Δ DUR | Δ Confidence | Δ DUR |
| | Specification | | Virginia Tech | | Confidence 1Y | | MSA-shooting | |
| Δ Confidence | | 0.953** | | 1.041*** | | 2.976** | | 0.594 |
| | | (0.459) | | (0.242) | | (1.187) | | (0.514) |
| Mass fatalities ($\geq 3$) | -0.034*** | | -0.039*** | | -0.018** | | -0.008*** | |
| | (0.010) | | (0.007) | | (0.007) | | (0.002) | |
| Δ Improved personal finances | 0.137*** | -0.080 | 0.059*** | -0.013 | 0.017*** | -0.000 | 0.056*** | 0.017 |
| | (0.005) | (0.062) | (0.006) | (0.019) | (0.004) | (0.026) | (0.007) | (0.031) |
| Δ County unemployment rate | -0.008 | 0.007 | -0.020 | 0.021 | 0.003 | -0.017 | -0.006 | 0.020 |
| | (0.013) | (0.020) | (0.019) | (0.023) | (0.014) | (0.042) | (0.026) | (0.025) |
| Initial confidence | -0.593*** | 0.535* | | | | | | |
| | (0.005) | (0.275) | | | | | | |
| Initial personal finances | 0.178*** | -0.162** | | | | | | |
| | (0.005) | (0.078) | | | | | | |
| Constant | 1.606*** | -1.088 | -0.027 | 0.331* | -0.330** | 1.244** | -0.248 | -0.300 |
| | (0.104) | (0.853) | (0.135) | (0.196) | (0.132) | (0.587) | (0.171) | (0.194) |
| Observations | 36,276 | 33,523 | 35,318 | 32,624 | 36,809 | 33,922 | 28,862 | 26,673 |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Location FE | MSA | MSA | MSA | MSA | MSA | MSA | MSA | MSA |
| SE cluster | State | State | MSA | MSA | MSA | MSA | State | MSA |
| Weight | Unweighted | Unweighted | HH head | HH head | HH head | HH head | HH head | HH head |
| Weak instrument test | | | | | | | | |
| F-statistic | 11.21 | | 32.96 | | 5.999 | | 13.08 | |

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure A.12: Robustness of 2nd Stage: Mass Shooting Dummy (County level)

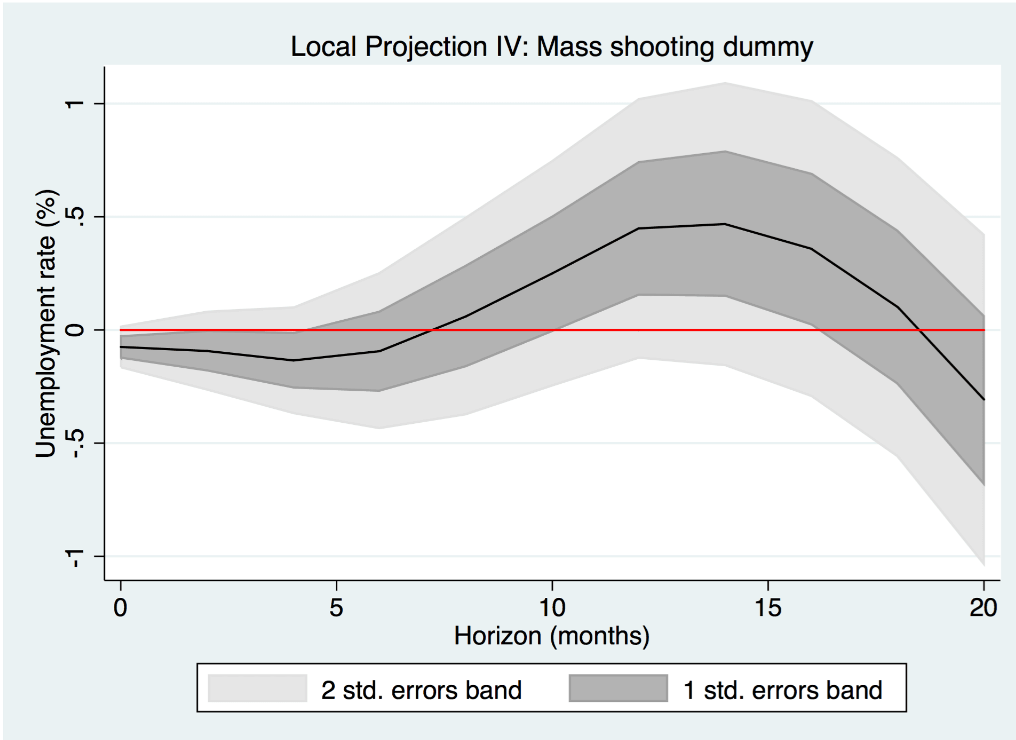



Figure A.13: Robustness of 2nd Stage: All Interview Respondents (County level)

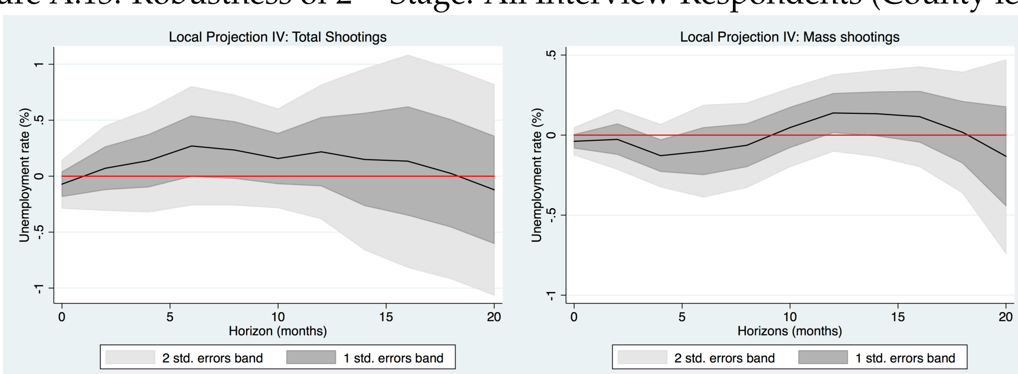
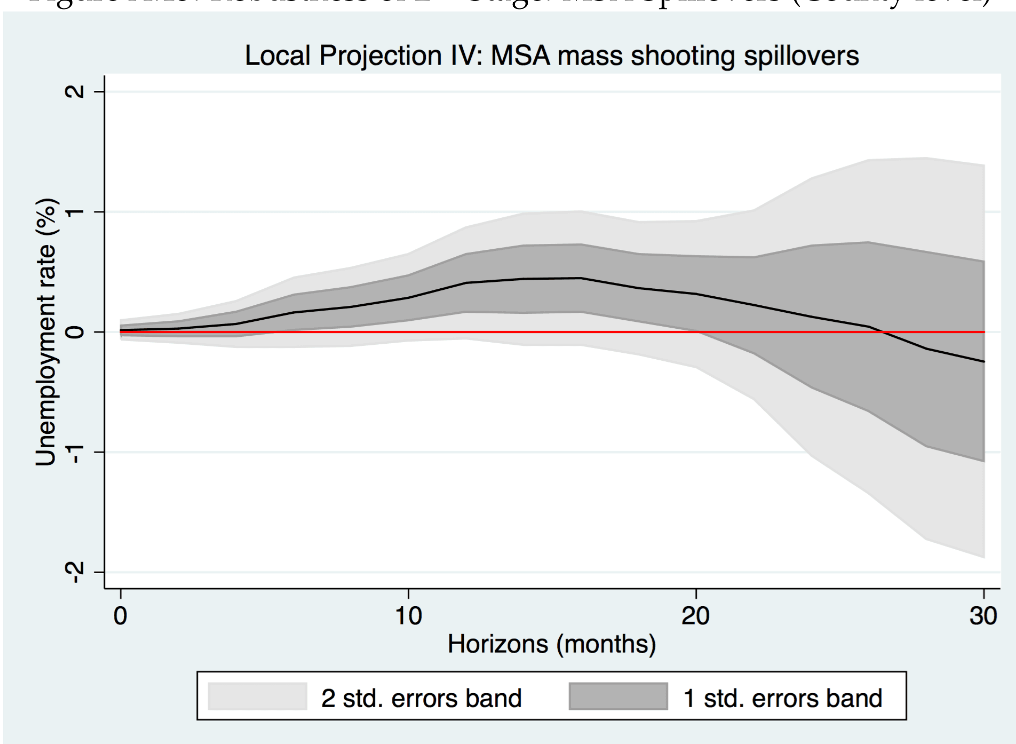


Figure A.14: Robustness of 2nd Stage: Confidence 1 Year Ahead (County level)


Figure A.15: Robustness of 2nd Stage: MSA Spillovers (County level)



## A.5 Heterogeneous Effects

Table A.27: Heterogeneous Effects in OLS (Individual level)

| | (1)<br>Δ Durables | (2)<br>Δ Cars | (3)<br>Δ Houses |
|---|---|---|---|
| Δ Confidence | 0.061 | 0.059 | 0.036 |
| | (0.060) | (0.059) | (0.070) |
| Δ Confidence x Female | 0.030** | -0.000 | -0.013 |
| | (0.012) | (0.013) | (0.016) |
| Δ Confidence x Age | -0.111 | -0.074 | 0.031 |
| | (0.225) | (0.216) | (0.233) |
| Δ Confidence x Age-squared | 0.087 | 0.101 | -0.048 |
| | (0.210) | (0.196) | (0.223) |
| Δ Confidence x Education | -0.004 | 0.005 | 0.006 |
| | (0.005) | (0.007) | (0.007) |
| Δ Confidence x Income quintile | 0.010** | -0.006 | -0.007 |
| | (0.005) | (0.006) | (0.005) |
| Constant | 0.285** | -0.069 | -0.394* |
| | (0.142) | (0.294) | (0.214) |
| Observations | 31,534 | 31,599 | 33,095 |
| R-squared | 0.039 | 0.035 | 0.036 |
| Individual controls | Yes | Yes | Yes |
| Δ personal finance & unemp. controls | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes |
| Location FE | MSA | MSA | MSA |
| SE cluster | state | state | state |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.28: Heterogeneous Effects of Sentiments in Response to Shootings

| | (1) Δ Confidence | (2) Δ Confidence | (3) Δ Confidence | (4) Δ Confidence | (5) Δ Confidence |
|---|---|---|---|---|---|
| Total shootings | -0.038*** | -0.017 | 0.146 | 0.045 | -0.098 |
| | (0.011) | (0.014) | (0.094) | (0.045) | (0.134) |
| Total shootings x Female | | -0.046 | | | |
| | | (0.037) | | | |
| Total shootings x Education | | | -0.035** | | |
| | | | (0.016) | | |
| Total shootings x Income quintile | | | | -0.022* | |
| | | | | (0.012) | |
| Total shootings x Age | | | | | 0.003 |
| | | | | | (0.046) |
| Total shootings x Age-squared | | | | | 0.002 |
| | | | | | (0.004) |
| Δ Improved personal finances | 0.060*** | 0.060*** | 0.060*** | 0.060*** | 0.058*** |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| Δ County unemployment rate | -0.021 | -0.021 | -0.020 | -0.021 | -0.017 |
| | (0.022) | (0.022) | (0.022) | (0.022) | (0.022) |
| Constant | 0.131 | 0.131 | 0.127 | 0.129 | -0.038 |
| | (0.168) | (0.168) | (0.168) | (0.169) | (0.186) |
| Observations | 34,023 | 34,023 | 34,023 | 34,023 | 34,023 |
| R-squared | 0.027 | 0.027 | 0.027 | 0.027 | 0.042 |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Location FE | No | No | No | No | No |
| Controls for indiv. characteristics | Yes | Yes | Yes | Yes | Yes |
| SE cluster | state | state | state | state | state |
| F-statistic | 11.09 | 5.589 | 8.631 | 4.295 | 6.815 |

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.30: Correlations Across County Characteristics

| | **Political culture** | | **Gun culture** | | | **Urban culture** | | |
|---|---|---|---|---|---|---|---|---|
| | REP | TW | CHECK | LAX | LOAD | RUR | NMR | CREAT |
| **Political culture** | | | | | | | | |
| Republicans (REP) | 1 | | | | | | | |
| TW voter ideology (TW) | 0.705 | 1 | | | | | | |
| **Gun culture** | | | | | | | | |
| No background check (CHECK) | 0.227 | 0.292 | 1 | | | | | |
| Lax gun control (LAX) | 0.333 | 0.392 | 0.707 | 1 | | | | |
| Loaded firearm (LOAD) | 0.236 | 0.342 | 0.515 | 0.743 | 1 | | | |
| **Urban culture** | | | | | | | | |
| Rurality and remoteness (RUR) | 0.332 | 0.331 | 0.115 | 0.231 | 0.085 | 1 | | |
| Net migration rate (NMR) | 0.061 | 0.082 | -0.001 | 0.062 | 0.136 | -0.067 | 1 | |
| Creative employment (CREAT) | -0.371 | -0.434 | -0.199 | -0.268 | -0.204 | -0.597 | 0.320 | 1 |

Table A.29: IV Heterogeneous Effects - Individual Characteristics

| Shooting IV: | (1) Total Stage 1 Δ Confidence | (2) Total Stage 2 Δ DUR | (3) Not dispute Stage 1 Δ Confidence | (4) Not dispute Stage 2 Δ DUR | (5) Open fire Stage 1 Δ Confidence | (6) Open fire Stage 2 Δ DUR | (7) Mass Stage 1 Δ Confidence | (8) Mass Stage 2 Δ DUR |
|---|---|---|---|---|---|---|---|---|
| Δ Confidence | | 0.905*** | | 1.034*** | | 0.856*** | | 0.973*** |
| | | (0.194) | | (0.218) | | (0.190) | | (0.159) |
| Shooting | 0.123*** | | 0.102** | | 0.088** | | 0.090*** | |
| | (0.046) | | (0.049) | | (0.042) | | (0.032) | |
| Shooting x Female | -0.070** | | -0.096*** | | -0.095*** | | -0.106*** | |
| | (0.032) | | (0.022) | | (0.018) | | (0.016) | |
| Shooting x Income quintile | -0.035*** | | -0.026** | | -0.026*** | | -0.023*** | |
| | (0.010) | | (0.010) | | (0.008) | | (0.007) | |
| Female | -0.019 | -0.005 | -0.019 | -0.002 | -0.020 | -0.006 | -0.020 | -0.004 |
| | (0.025) | (0.033) | (0.025) | (0.034) | (0.025) | (0.031) | (0.025) | (0.032) |
| Income quintile | 0.009 | -0.001 | 0.008 | -0.002 | 0.008 | -0.001 | 0.008 | -0.002 |
| | (0.008) | (0.011) | (0.008) | (0.012) | (0.008) | (0.011) | (0.008) | (0.012) |
| Δ Improved personal finances | 0.061*** | -0.008 | 0.061*** | -0.016 | 0.061*** | -0.005 | 0.061*** | -0.012 |
| | (0.006) | (0.014) | (0.006) | (0.016) | (0.006) | (0.013) | (0.006) | (0.012) |
| Δ County unemployment rate | -0.013 | 0.003 | -0.013 | 0.005 | -0.013 | 0.003 | -0.013 | 0.004 |
| | (0.021) | (0.022) | (0.020) | (0.024) | (0.021) | (0.022) | (0.020) | (0.023) |
| Constant | 0.124 | 0.223 | 0.124 | 0.207 | 0.124 | 0.229 | 0.124 | 0.215 |
| | (0.149) | (0.191) | (0.148) | (0.204) | (0.148) | (0.185) | (0.148) | (0.197) |
| Observations | 32,100 | 32,100 | 32,100 | 32,100 | 32,100 | 32,100 | 32,100 | 32,100 |
| R-squared | 0.044 | -0.583 | 0.044 | -0.787 | 0.044 | -0.514 | 0.044 | -0.687 |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Location FE | MSA | MSA | MSA | MSA | MSA | MSA | MSA | MSA |
| SE cluster | MSA | MSA | MSA | MSA | MSA | MSA | MSA | MSA |
| F-statistic | 10.48 | | 15.92 | | 15.79 | | 25.99 | |

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.31: Heterogeneous Effects - Political and Gun Culture

| | (1)<br>Δ Confidence | (2)<br>Δ Confidence | (3)<br>Δ Confidence | (4)<br>Δ Confidence | (5)<br>Δ Confidence |
|---|---|---|---|---|---|
| Total shootings | -0.212*** | 0.040 | -0.059*** | -0.094*** | -0.095*** |
| | (0.060) | (0.054) | (0.019) | (0.027) | (0.030) |
| Total shootings x Republicans | 0.472** | | | | |
| | (0.184) | | | | |
| Total shootings x TW voter ideology | | 0.276 | | | |
| | | (0.165) | | | |
| Total shootings x No background check | | | 0.297** | | |
| | | | (0.133) | | |
| Total shootings x Lax gun control | | | | 0.033** | |
| | | | | (0.016) | |
| Total shootings x Loaded firearm | | | | | 2.568** |
| | | | | | (1.203) |
| Republicans | 0.148 | | | | |
| | (0.092) | | | | |
| TW voter ideology | | 0.083** | | | |
| | | (0.040) | | | |
| No background check | | | 0.032 | | |
| | | | (0.021) | | |
| Lax gun control | | | | 0.006* | |
| | | | | (0.003) | |
| Loaded firearm | | | | | 0.624* |
| | | | | | (0.328) |
| Δ Improved personal finances | 0.049*** | 0.050*** | 0.049*** | 0.050*** | 0.057*** |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.007) |
| Constant | 0.182 | 0.257 | 0.224 | 0.213 | 0.348* |
| | (0.212) | (0.199) | (0.196) | (0.193) | (0.194) |
| Observations | 30,978 | 30,903 | 30,979 | 30,903 | 28,683 |
| R-squared | 0.045 | 0.045 | 0.045 | 0.045 | 0.045 |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Location FE | No | No | No | No | No |
| SE cluster | state | state | state | state | state |
| F-statistic | 12.56 | 11.71 | 6.554 | 6.059 | 5.791 |

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.32: Heterogeneous Effects - Urban Culture

| | (1)<br>Δ Confidence | (2)<br>Δ Confidence | (3)<br>Δ Confidence |
|---|---|---|---|
| Total shootings | -0.075*** | -0.025 | -0.288*** |
| | (0.020) | (0.016) | (0.092) |
| Total shootings x Rurality & remoteness | 0.022** | | |
| | (0.010) | | |
| Total shootings x Net migration rate | | 0.890** | |
| | | (0.377) | |
| Total shootings x Creative employment | | | 0.747** |
| | | | (0.281) |
| Rurality & remoteness | 0.003 | | |
| | (0.006) | | |
| Net migration rate | | 0.207* | |
| | | (0.103) | |
| Creative employment | | | -0.223 |
| | | | (0.180) |
| Δ Improved personal finances | 0.050*** | 0.050*** | 0.049*** |
| | (0.009) | (0.009) | (0.009) |
| Constant | 0.238 | 0.234 | 0.303* |
| | (0.198) | (0.201) | (0.179) |
| Observations | 30,669 | 30,254 | 30,979 |
| R-squared | 0.045 | 0.045 | 0.045 |
| Time FE | Yes | Yes | Yes |
| Location FE | No | No | No |
| SE cluster | state | state | state |
| F-statistic | 13.54 | 37.50 | 10.62 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.33: Determinants of Shootings Controlling for Population

| | (1)<br>Shootings | (2)<br>Shootings | (3)<br>Shootings | (4)<br>Shootings | (5)<br>Shootings | (6)<br>Shootings |
|---|---|---|---|---|---|---|
| Lax gun control | -0.110*** | 0.061*** | | | | 0.052*** |
| | (0.011) | (0.011) | | | | (0.011) |
| Metro area | | | 1.210*** | -0.165*** | | |
| | | | (0.058) | (0.062) | | |
| Population density | | | | | -0.226*** | -0.238*** |
| | | | | | (0.030) | (0.025) |
| Population | | 0.727*** | | 0.726*** | 0.750*** | 0.760*** |
| | | (0.010) | | (0.010) | (0.010) | (0.010) |
| Constant | 1.275*** | -0.594*** | 0.081** | -0.093*** | -0.128*** | -0.508*** |
| | (0.080) | (0.086) | (0.081) | (0.035) | (0.030) | (0.086) |
| Observations | 687,544 | 664,200 | 678,672 | 664,416 | 663,552 | 663,336 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

# Appendix B

# Appendix: Does Economic Security Really Impact on Gun Violence at U.S. Schools?

## B.1 Figures and Tables

Figure B.2: Mass Shootings Histogram

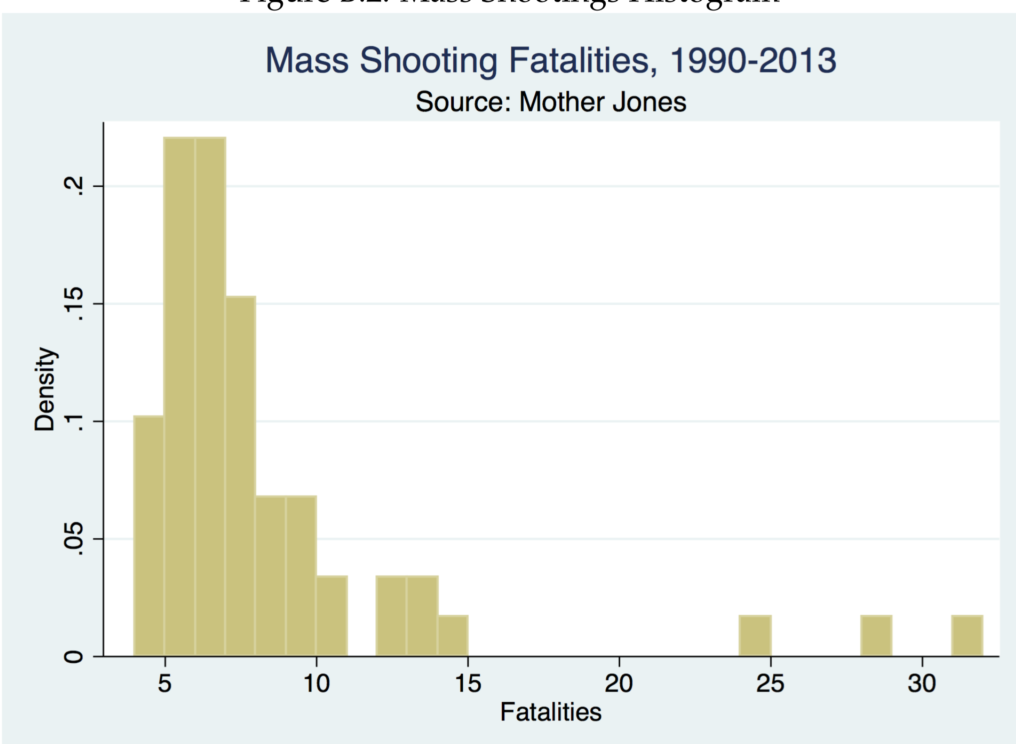


Figure B.1: Shootings in U.S. Counties

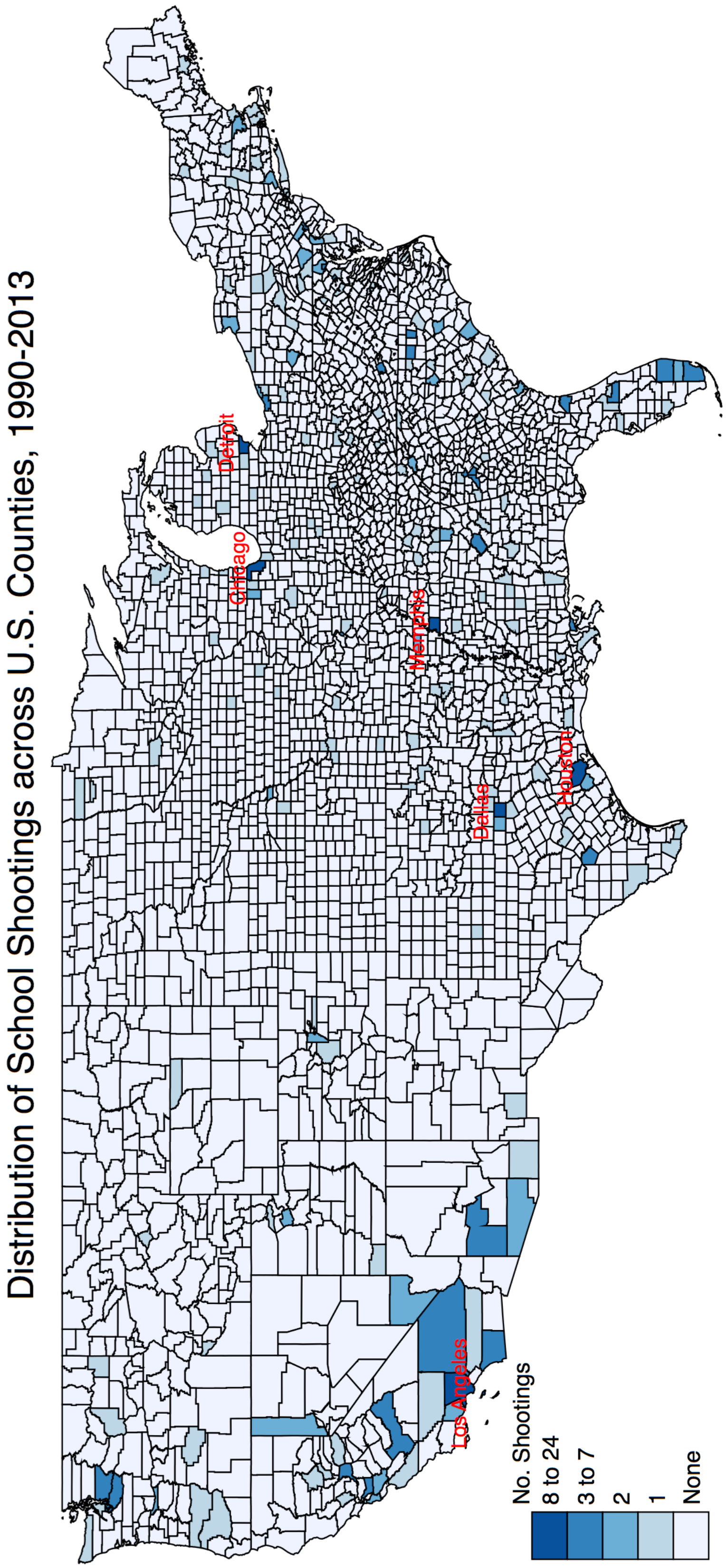


Figure B.3: Correlation for Trend vs. Cyclical Components

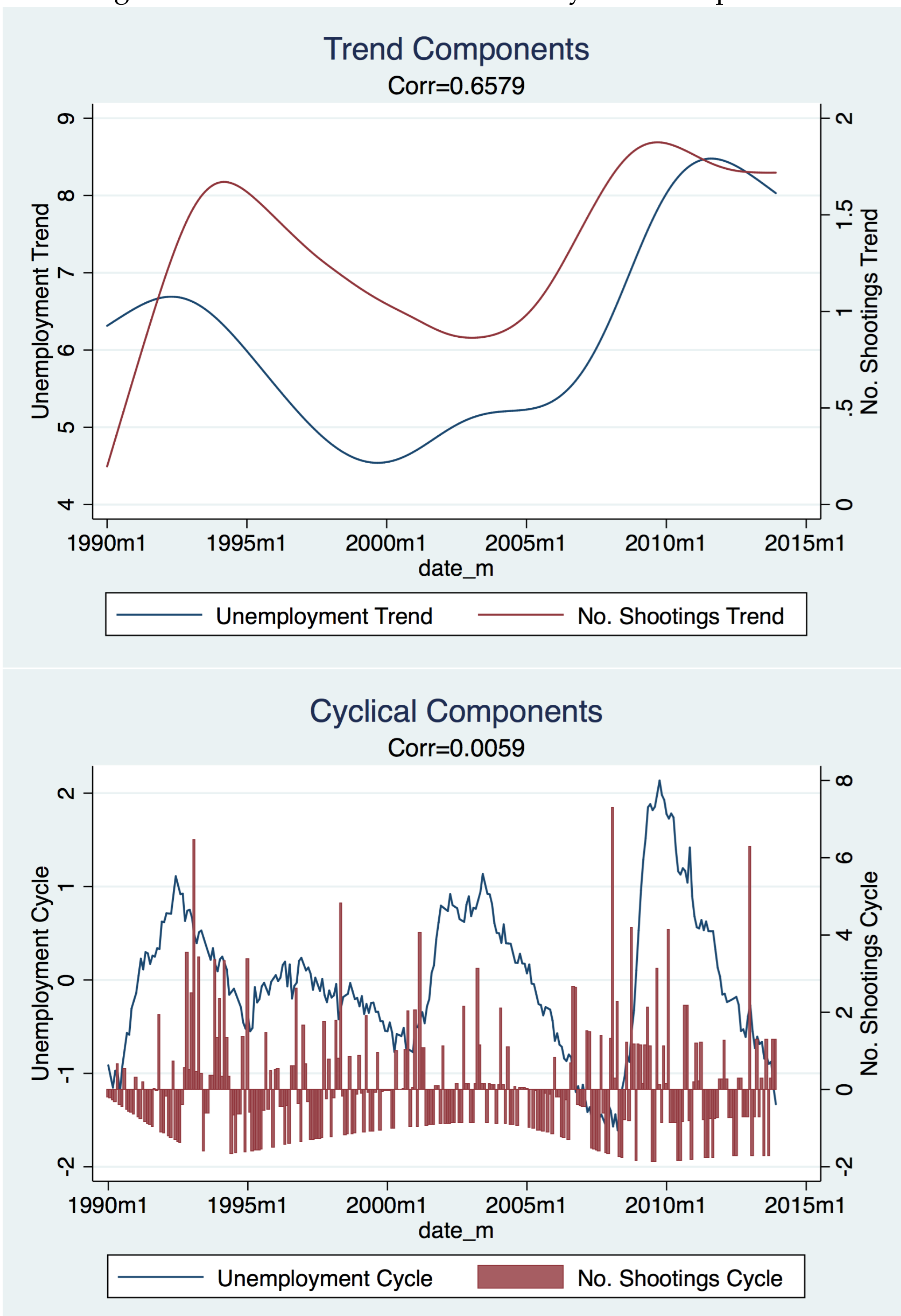


Figure B.4: Spurious Correlation: t-statistics for 10,000 Random Walks

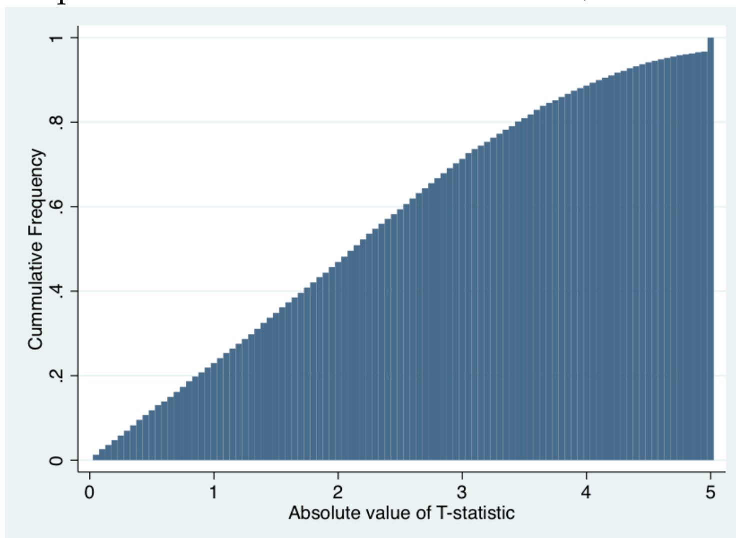



Figure B.5: Timing of 3 Deadliest Mass Shootings

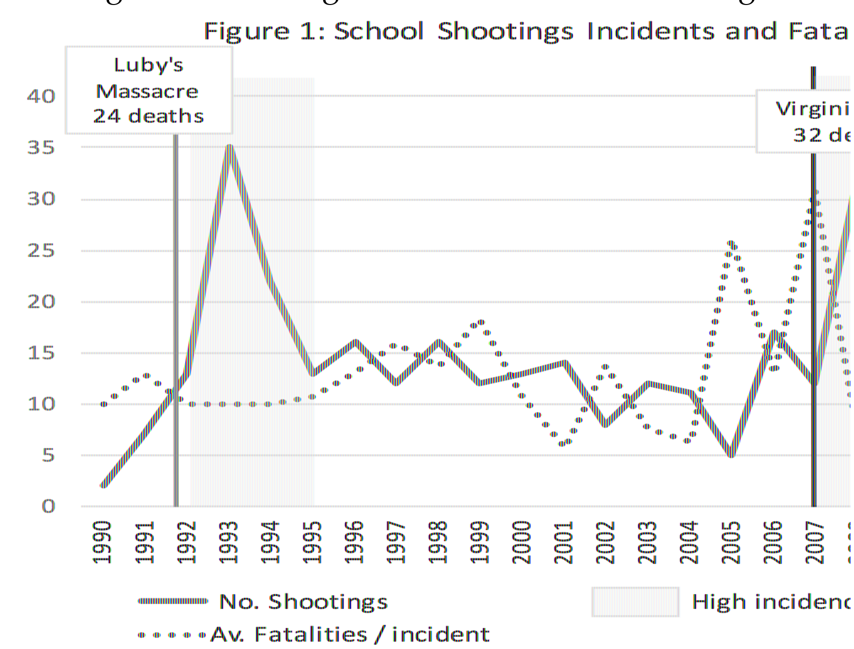


Figure B.6: Canada: School Shootings vs. Unemployment

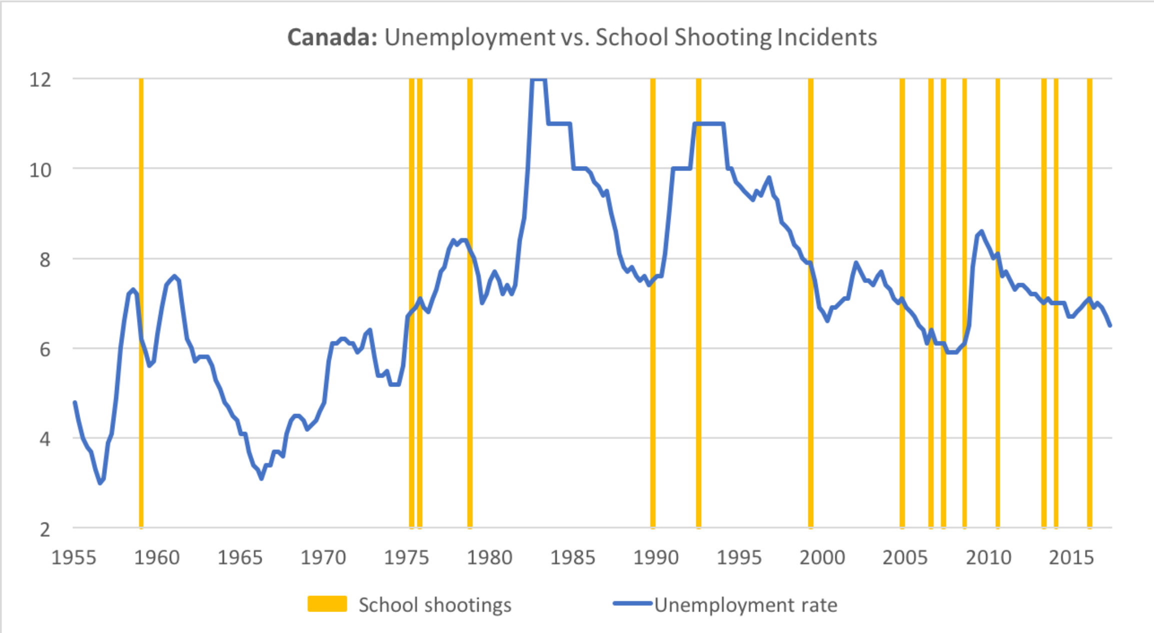



Table B.1: Poisson Regression - Baseline

| | (1) National No. Shootings | (2) Regional No. Shootings | (3) Regional No. Shootings | (4) County No. Shootings | (5) County No. Shootings |
|---|---|---|---|---|---|
| Unemployment | 0.112*** | 0.105*** | 0.0357 | 0.0837*** | 0.0314 |
| | (0.0300) | (0.0293) | (0.107) | (0.0238) | (0.0410) |
| Summer | -1.161*** | -1.153*** | | -1.159*** | |
| | (0.175) | (0.175) | | (0.175) | |
| Constant | -0.236 | -2.072*** | -20.81 | -6.515*** | -23.19 |
| | (0.200) | (0.221) | (11,600) | (1.046) | (4,640) |
| Observations | 288 | 2,016 | 2,016 | 61,344 | 61,344 |
| No. geographical units | 1 | 7 | 7 | 213 | 213 |
| Location fixed effects | | ✓ | ✓ | ✓ | ✓ |
| Time fixed effects | | | ✓ | | ✓ |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.2: Poisson Regression - Controlling for Sub-periods and Mass Shootings

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Geographical unit | National | Regional | County | National | Regional | County | National | National |
| Dependent variable | No. Shootings | No. Shootings | No. Shootings | No. Shootings | No. Shootings | No. Shootings | No. Shootings | No. Shootings |
| Mass definition | | | | MJ (Top 3) | MJ (Top 3) | MJ (Top 3) | MJ (All) | Duwe (All) |
| Unemployment | -0.0167 | -0.00824 | 0.00895 | 0.0270 | -0.00396 | 0.0281 | 0.0746 | 0.0235 |
| | (0.0429) | (0.0410) | (0.0298) | (0.0378) | (0.0361) | (0.0278) | (0.0502) | (0.0464) |
| 1992-1994 | 1.939*** | 1.936*** | 1.931*** | | | | | |
| | (0.306) | (0.306) | (0.306) | | | | | |
| 1994-2007 | 0.918*** | 0.925*** | 0.956*** | | | | | |
| | (0.296) | (0.295) | (0.292) | | | | | |
| 2007-2013 | 1.541*** | 1.525*** | 1.510*** | | | | | |
| | (0.293) | (0.293) | (0.292) | | | | | |
| Within 1-12 months of 3 deadliest shootings | | | | 0.615*** | 0.509*** | 0.614*** | 0.0068** | 0.0131*** |
| | | | | (0.166) | (0.157) | (0.165) | (0.003) | (0.004) |
| Within 13-24 months of 3 deadliest shootings | | | | 0.774*** | 0.951*** | 0.771*** | 0.0114*** | 0.0116** |
| | | | | (0.171) | (0.162) | (0.166) | (0.004) | (0.005) |
| Within 25-36 months of 3 deadliest shootings | | | | 0.698*** | 0.885*** | 0.694*** | 0.0025 | 0.0059 |
| | | | | (0.186) | (0.179) | (0.173) | (0.005) | (0.006) |
| Within 37-48 months of 3 deadliest shootings | | | | 0.262 | 0.430** | 0.258 | -0.005 | 0.004 |
| | | | | (0.202) | (0.198) | (0.196) | (0.005) | (0.005) |
| Summer | -1.107*** | -1.101*** | -1.108*** | -1.131*** | -1.153*** | -1.131*** | -1.123*** | -1.070*** |
| | (0.175) | (0.176) | (0.175) | (0.178) | (0.175) | (0.178) | (0.178) | (0.184) |
| Constant | -0.620 | -2.589*** | -6.783*** | 0.0982 | -1.747*** | -5.963*** | -0.248*** | -0.499** |
| | (0.396) | (0.395) | (1.103) | (0.220) | (0.237) | (1.054) | (0.213) | (0.221) |
| Pseudo R-squared | 0.146 | 0.139 | 0.0889 | 0.115 | 0.127 | 0.0863 | 0.0991 | 0.0941 |
| Observations | 288 | 2,016 | 61,344 | 252 | 2,016 | 53,676 | 252 | 240 |
| No. geographical units | 1 | 7 | 213 | 1 | 7 | 213 | 1 | 1 |
| Location fixed effects | | ✓ | ✓ | | ✓ | ✓ | | |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.3: Poisson Regression - By Sub-period

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Time sample | 1990-1992 | 1992-1994 | 1994-2007 | 2007-2013 |
| Geographical unit | National | National | National | National |
| Dependent variable | No. Shootings | No. Shootings | No. Shootings | No. Shootings |
| Unemployment | 0.547 | 0.184 | -0.186 | -0.00419 |
| | (0.402) | (0.348) | (0.122) | (0.0470) |
| Summer | -1.606 | -1.639** | -1.023*** | -1.059*** |
| | (1.045) | (0.719) | (0.257) | (0.265) |
| Constant | -4.363 | -0.0371 | 1.137* | 0.819** |
| | (2.770) | (2.397) | (0.610) | (0.374) |
| Pseudo R-squared | 0.0953 | 0.117 | 0.0551 | 0.0680 |
| Observations | 33 | 20 | 153 | 82 |
| | (1) | (2) | (3) | (4) |
| Time sample | 1990-1992 | 1992-1994 | 1994-2007 | 2007-2013 |
| Geographical unit | Regional | Regional | Regional | Regional |
| Dependent variable | No. Shootings | No. Shootings | No. Shootings | No. Shootings |
| Unemployment | 0.500 | 0.146 | -0.195 | -0.00215 |
| | (0.402) | (0.358) | (0.120) | (0.0462) |
| Summer | -1.542 | -1.640** | -1.017*** | -1.052*** |
| | (1.041) | (0.719) | (0.257) | (0.265) |
| Constant | -5.602* | -1.559 | -0.603 | -1.501*** |
| | (2.901) | (2.461) | (0.593) | (0.418) |
| Pseudo R-squared | 0.172 | 0.104 | 0.0870 | 0.156 |
| Observations | 231 | 140 | 1,071 | 574 |
| Region FE | ✓ | ✓ | ✓ | ✓ |
| | (1) | (2) | (3) | (4) |
| Time sample | 1990-1992 | 1992-1994 | 1994-2007 | 2007-2013 |
| Geographical unit | County | County | County | County |
| Dependent variable | No. Shootings | No. Shootings | No. Shootings | No. Shootings |
| Unemployment | - | 0.147 | -0.0566 | 0.00419 |
| | - | (0.211) | (.0635) | (0.0416) |
| Summer | - | -1.629** | -1.033*** | -1.059*** |
| | | (0.719) | (0.257) | (0.265) |
| Constant | - | -26.282 | -24.294 | -4.283*** |
| | - | (41371) | (22256) | (1.162) |
| Pseudo R-squared | - | 0.3277 | 0.1444 | 0.1696 |
| Observations | - | 4,260 | 32,589 | 17,466 |
| County FE | - | ✓ | ✓ | ✓ |

Note: A Poisson regression could not be estimated at the county level for sub-period 1990-1992 due to non-concavity of the likelihood function.

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table B.4: Panel Regression - Impact of Past National Shootings

| | (1) | (2) | (3) |
|---|---|---|---|
| Geographical unit | National | Regional | County |
| Dependent variable | No. Shootings | No. Shootings | No. Shootings |
| No. National Shootings (-1) | 0.172*** | 0.0239*** | 0.000806*** |
| | (0.0574) | (0.00692) | (0.000217) |
| Summer | -0.949*** | -0.135*** | -0.00445*** |
| | (0.204) | (0.0245) | (0.000768) |
| Constant | 1.336*** | 0.191*** | 0.00627*** |
| | (0.132) | (0.0160) | (0.000499) |
| R-squared | 0.1235 | 0.0251 | 0.0010 |
| Observations | 287 | 2,009 | 61,131 |
| No. geographical units | 1 | 7 | 213 |
| Location fixed effects | | ✓ | ✓ |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.5: Panel Regression - Impact of Past Local Shootings

| | (1) | (2) | (3) |
|---|---|---|---|
| Geographical unit | National | Regional | County |
| Dependent variable | No. Shootings | No. Shootings | No. Shootings |
| No. Shootings (-1) | 0.172*** | 0.0509** | 0.00239 |
| | (0.0574) | (0.0223) | (0.00407) |
| Summer | -0.949*** | -0.149*** | -0.00515*** |
| | (0.204) | (0.0240) | (0.000745) |
| Constant | 1.336*** | 0.216*** | 0.00749*** |
| | (0.132) | (0.0129) | (0.000374) |
| R-squared | 0.1235 | 0.0284 | 0.0008 |
| Observations | 287 | 2,009 | 61,131 |
| No. geographical units | 1 | 7 | 213 |
| Location fixed effects | | ✓ | ✓ |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.6: Poisson Regression - Controlling for 3 Deadliest Shootings

| | (1) | (2) | (3) |
|---|---|---|---|
| Geographical unit | National | Regional | County |
| Dependent variable | No. Shootings | No. Shootings | No. Shootings |
| Unemployment | 0.0356 | 0.0350 | 0.0357 |
| | (0.0343) | (0.0332) | (0.0258) |
| Summer | -1.157*** | -1.150*** | -1.156*** |
| | (0.175) | (0.175) | (0.175) |
| Luby | 0.598*** | 0.615*** | 0.599*** |
| | (0.144) | (0.142) | (0.141) |
| Virginia Tech | 0.653*** | 0.662*** | 0.651*** |
| | (0.146) | (0.146) | (0.141) |
| Sandy Hook | 0.691*** | 0.706*** | 0.688*** |
| | (0.215) | (0.214) | (0.212) |
| Constant | 0.00742 | -1.897*** | -6.156*** |
| | (0.211) | (0.231) | (1.050) |
| Pseudo R-squared | 0.108 | 0.122 | 0.0812 |
| Observations | 288 | 2,016 | 61,344 |
| No. geographical units | 1 | 7 | 213 |
| Location fixed effects | | ✓ | ✓ |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.7: Alternative Definitions of Mass Shootings

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | National | National | National | National |
| Dependent variable | No. Shootings | No. Shootings | No. Shootings | No. Shootings |
| Unemployment | 0.0270 | 0.0192 | -0.0283 | 0.0746 |
| | (0.0378) | (0.0409) | (0.0460) | (0.0502) |
| Within 1-12 months of 3 deadliest shootings (dummy) | 0.615*** | | | |
| | (0.166) | | | |
| Within 13-24 months of 3 deadliest shootings (dummy) | 0.774*** | | | |
| | (0.171) | | | |
| Within 25-36 months of 3 deadliest shootings (dummy) | 0.698*** | | | |
| | (0.186) | | | |
| Within 37-48 months of 3 deadliest shootings (dummy) | 0.262 | | | |
| | (0.202) | | | |
| Within 1-12 months of 3 deadliest shootings (fatalities) | | 0.0200*** | | |
| | | (0.00550) | | |
| Within 13-24 months of 3 deadliest shootings (fatalities) | | 0.0257*** | | |
| | | (0.00604) | | |
| Within 25-36 months of 3 deadliest shootings (fatalities) | | 0.0243*** | | |
| | | (0.00701) | | |
| Within 37-48 months of 3 deadliest shootings (fatalities) | | 0.00999 | | |
| | | (0.00735) | | |
| Within 1-12 months of 10 deadliest shootings (fatalities) | | | 0.0134*** | |
| | | | (0.00447) | |
| Within 13-24 months of 10 deadliest shootings (fatalities) | | | 0.0253*** | |
| | | | (0.00532) | |
| Within 25-36 months of 10 deadliest shootings (fatalities) | | | 0.0180*** | |
| | | | (0.00622) | |
| Within 37-48 months of 10 deadliest shootings (fatalities) | | | 0.00217 | |
| | | | (0.00561) | |
| No. mass shooting fatalities in last 1-12 months | | | | 0.00675** |
| | | | | (0.00299) |
| No. mass shooting fatalities in last 13-24 months | | | | 0.0115*** |
| | | | | (0.00407) |
| No. mass shooting fatalities in last 25-36 months | | | | 0.00253 |
| | | | | (0.00531) |
| No. mass shooting fatalities in last 37-48 months | | | | -0.00485 |
| | | | | (0.00515) |
| Summer | -1.131*** | -1.129*** | -1.118*** | -1.127*** |
| | (0.178) | (0.178) | (0.178) | (0.178) |
| Constant | 0.0982 | 0.155 | 0.191 | -0.248 |
| | (0.220) | (0.233) | (0.216) | (0.213) |
| Observations | 252 | 252 | 252 | 252 |
| Pseudo R-squared | 0.115 | 0.111 | 0.112 | 0.0991 |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.8: Gun Purchases (NICS Background Checks)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Geographical unit | National | National | National | National |
| Mass shooting definition | 3 deadliest | 3 deadliest (weighted) | 10 deadliest (weighted) | Mass fatalities |
| Dependent variable | %ΔGun purchases | %ΔGun purchases | %ΔGun purchases | %ΔGun purchases |
| Mass shooting (-1) | 36.38*** | 1.169*** | 0.852*** | 0.715*** |
| | (7.454) | (0.250) | (0.222) | (0.183) |
| Mass shooting (-2) | 20.72*** | 0.685*** | 0.523** | 0.456** |
| | (7.454) | (0.250) | (0.222) | (0.183) |
| Mass shooting (-3) | 15.67** | 0.513** | 0.303 | 0.334* |
| | (7.454) | (0.250) | (0.222) | (0.181) |
| Mass shooting (-4) | 8.210 | 0.263 | 0.321 | 0.370** |
| | (7.454) | (0.250) | (0.227) | (0.184) |
| Mass shooting (-5) | -0.0585 | -0.00811 | 0.217 | 0.398** |
| | (7.454) | (0.250) | (0.227) | (0.182) |
| Mass shooting (-6) | -3.835 | -0.119 | 0.0719 | 0.181 |
| | (7.454) | (0.250) | (0.228) | (0.181) |
| Mass shooting (-7) | -4.788 | -0.153 | -0.215 | -0.0482 |
| | (7.454) | (0.250) | (0.228) | (0.182) |
| Mass shooting (-8) | -10.35 | -0.337 | -0.148 | -0.0804 |
| | (7.454) | (0.250) | (0.220) | (0.180) |
| Mass shooting (-9) | -5.183 | -0.161 | -0.206 | -0.0309 |
| | (7.454) | (0.250) | (0.220) | (0.181) |
| Mass shooting (-10) | 1.945 | 0.0722 | -0.131 | 0.00945 |
| | (7.454) | (0.250) | (0.221) | (0.181) |
| Mass shooting (-11) | -7.609 | -0.234 | -0.344 | -0.221 |
| | (7.454) | (0.250) | (0.221) | (0.182) |
| Mass shooting (-12) | -15.62** | -0.471* | -0.449** | -0.339* |
| | (7.454) | (0.250) | (0.221) | (0.182) |
| Constant | 5.773*** | 5.759*** | 5.658*** | 2.867** |
| | (0.870) | (0.878) | (1.002) | (1.295) |
| Observations | 169 | 169 | 169 | 169 |
| R-squared | 0.228 | 0.213 | 0.168 | 0.194 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.9: Poisson Regression - Mass Shootings

| | (1) | (2) |
|---|---|---|
| | National (MJ) | National (Duwe) |
| VARIABLES | No. mass shootings | No. mass shootings |
| Unemployment | 0.0862 | 0.0436 |
| | (0.0771) | (0.0635) |
| Summer | -0.269 | 0.0136 |
| | (0.323) | (0.241) |
| Constant | -2.063*** | -1.425*** |
| | (0.511) | (0.414) |
| Observations | 288 | 288 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.10: Consumer Confidence and Job Flows

| | (1) | (2) | (3) |
|---|---|---|---|
| Geographical unit | National | National | National |
| Dependent variable | No. Shootings | No. Shootings | No. Shootings |
| Consumer confidence index | -0.0939*** | | |
| | (0.0338) | | |
| Job finding rate (UE/U) | | -3.936*** | |
| | | (1.065) | |
| Separation rate (EU/E) | | | 70.70*** |
| | | | (26.60) |
| Summer | -1.155*** | -1.164*** | -1.166*** |
| | (0.175) | (0.175) | (0.175) |
| Constant | 9.842*** | 1.445*** | -0.548 |
| | (3.371) | (0.265) | (0.390) |
| Pseudo R-squared | 0.0703 | 0.0771 | 0.0703 |
| Observations | 288 | 287 | 287 |
| No. geographical units | 1 | 1 | 1 |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.11: Consumer Confidence and Job Flows - Sub-period Intercepts

| | (1) | (2) | (3) |
|---|---|---|---|
| Geographical unit | National | National | National |
| Dependent variable | No. Shootings | No. Shootings | No. Shootings |
| Consumer confidence index | 0.0134 | | |
| | (0.0585) | | |
| Job finding rate (bop) | | 1.259 | |
| | | (1.626) | |
| Separation rate (bop) | | | 40.14 |
| | | | (32.91) |
| Summer | -1.107*** | -1.109*** | -1.111*** |
| | (0.176) | (0.175) | (0.175) |
| 1992-1994 | 1.921*** | 1.909*** | 1.928*** |
| | (0.311) | (0.307) | (0.307) |
| 1994-2007 | 0.915*** | 0.869*** | 1.035*** |
| | (0.313) | (0.292) | (0.307) |
| 2007-2013 | 1.530*** | 1.552*** | 1.540*** |
| | (0.291) | (0.302) | (0.292) |
| Constant | -2.053 | -1.012** | -1.353** |
| | (5.800) | (0.498) | (0.610) |
| Pseudo R-squared | 0.146 | 0.145 | 0.146 |
| Observations | 288 | 287 | 287 |
| No. geographical units | 1 | 1 | 1 |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.12: Consumer Confidence and Job Flows - Controlling for 3 Deadliest Shootings I

| | (1) | (2) | (3) |
|---|---|---|---|
| Geographical unit | National | National | National |
| Dependent variable | No. Shootings | No. Shootings | No. Shootings |
| Consumer confidence index | -0.00469 | | |
| | (0.0431) | | |
| Job finding rate (UE/U) | | -0.645 | |
| | | (1.231) | |
| Separation rate (EU/E) | | | 51.15 |
| | | | (41.45) |
| Within 1-12 months of 3 deadliest shootings | 0.626*** | 0.608*** | 0.652*** |
| | (0.180) | (0.171) | (0.164) |
| Within 13-24 months of 3 deadliest shootings | 0.808*** | 0.789*** | 0.659*** |
| | (0.194) | (0.169) | (0.206) |
| Within 25-36 months of 3 deadliest shootings | 0.764*** | 0.734*** | 0.619*** |
| | (0.166) | (0.170) | (0.198) |
| Within 37-48 months of 3 deadliest shootings | 0.313 | 0.289 | 0.205 |
| | (0.193) | (0.194) | (0.207) |
| Summer | -1.134*** | -1.132*** | -1.131*** |
| | (0.178) | (0.178) | (0.178) |
| Constant | 0.717 | 0.418 | -0.435 |
| | (4.345) | (0.340) | (0.558) |
| R-squared | 0.1142 | 0.1145 | 0.1160 |
| Observations | 252 | 252 | 252 |
| No. geographical units | 1 | 1 | 1 |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.13: Consumer Confidence and Job Flows - Controlling for 3 Deadliest Shootings II

| | (1) | (2) | (3) |
|---|---|---|---|
| Geographical unit | National | National | National |
| Dependent variable | No. Shootings | No. Shootings | No. Shootings |
| Consumer confidence index | 0.0322 | | |
| | (0.0435) | | |
| Job finding rate (bop) | | -1.360 | |
| | | (1.269) | |
| Separation rate (bop) | | | 6.264 |
| | | | (29.83) |
| Summer | -1.161*** | -1.160*** | -1.162*** |
| | (0.175) | (0.175) | (0.175) |
| Luby | 0.668*** | 0.607*** | 0.622*** |
| | (0.143) | (0.140) | (0.151) |
| Virginia Tech | 0.788*** | 0.638*** | 0.693*** |
| | (0.171) | (0.148) | (0.145) |
| Sandy Hook | 0.794*** | 0.644*** | 0.746*** |
| | (0.217) | (0.227) | (0.208) |
| Constant | -3.021 | 0.576* | 0.132 |
| | (4.371) | (0.339) | (0.419) |
| Pseudo R-squared | 0.108 | 0.108 | 0.107 |
| Observations | 288 | 287 | 287 |
| No. geographical units | 1 | 1 | 1 |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.14: Robust SE - Baseline

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Geographical unit | National | Regional | County | County |
| Dependent variable | No. Shootings | No. Shootings | No. Shootings | No. Shootings |
| Unemployment | 0.112*** | 0.105*** | 0.0837*** | 0.0837*** |
| | (0.0354) | (0.0298) | (0.0254) | (0.0209) |
| Summer | -1.161*** | -1.153*** | -1.159*** | -1.159*** |
| | (0.196) | (0.184) | (0.175) | (0.140) |
| Constant | -0.236 | -2.072*** | -6.515*** | -6.515*** |
| | (0.244) | (0.224) | (1.029) | (0.269) |
| Pseudo R-squared | 0.0762 | 0.107 | 0.0742 | - |
| Observations | 288 | 2,016 | 61,344 | 61,344 |
| No. geographical units | 1 | 7 | 213 | 213 |
| Standard error adjustment | Robust | Robust | Robust | State Cluster |
| Location fixed effects | | ✓ | ✓ | ✓ |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.15: Robust SE - By Sub-period

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Time sample | 1990-1992 | 1992-1994 | 1994-2007 | 2007-2013 |
| Geographical unit | National | National | National | National |
| Dependent variable | No. Shootings | No. Shootings | No. Shootings | No. Shootings |
| Unemployment | 0.547 | 0.184 | -0.186 | -0.00419 |
| | (0.380) | (0.264) | (0.132) | (0.0657) |
| Summer | -1.606 | -1.639*** | -1.023*** | -1.059*** |
| | (1.118) | (0.444) | (0.237) | (0.338) |
| Constant | -4.363* | -0.0371 | 1.137* | 0.819 |
| | (2.571) | (1.775) | (0.667) | (0.550) |
| Pseudo R-squared | 0.0953 | 0.117 | 0.0551 | 0.0680 |
| Observations | 33 | 20 | 153 | 82 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.16: Robust SE - Sub-period Intercepts

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Geographical unit | National | Regional | County | County |
| Dependent variable | No. Shootings | No. Shootings | No. Shootings | No. Shootings |
| Unemployment | -0.0167 | -0.00824 | 0.00895 | 0.00895 |
| | (0.0572) | (0.0456) | (0.0319) | (0.0268) |
| Summer | -1.107*** | -1.101*** | -1.108*** | -1.108*** |
| | (0.190) | (0.183) | (0.175) | (0.140) |
| 1992-1994 | 1.939*** | 1.936*** | 1.931*** | 1.931*** |
| | (0.322) | (0.315) | (0.307) | (0.395) |
| 1994-2007 | 0.918*** | 0.925*** | 0.956*** | 0.956*** |
| | (0.319) | (0.307) | (0.289) | (0.348) |
| 2007-2013 | 1.541*** | 1.525*** | 1.510*** | 1.510*** |
| | (0.329) | (0.312) | (0.293) | (0.396) |
| Constant | -0.620 | -2.589*** | -6.783*** | -6.783*** |
| | (0.472) | (0.408) | (1.083) | (0.443) |
| Pseudo R-squared | 0.146 | 0.139 | 0.0889 | - |
| Observations | 288 | 2,016 | 61,344 | 61,344 |
| No. geographical units | 1 | 7 | 213 | 213 |
| Standard error adjustment | Robust | Robust | Robust | State Cluster |
| Location fixed effects | | ✓ | ✓ | ✓ |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.17: Robust SE - Controlling for 3 Deadliest Shootings I

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Geographical unit | National | Regional | County | County |
| Dependent variable | No. Shootings | No. Shootings | No. Shootings | No. Shootings |
| Unemployment | 0.0270 | -0.00396 | 0.0281 | 0.0281 |
| | (0.0418) | (0.0370) | (0.0284) | (0.0228) |
| Summer | -1.131*** | -1.153*** | -1.131*** | -1.131*** |
| | (0.192) | (0.184) | (0.178) | (0.141) |
| Within 1-12 months of 3 deadliest shootings | 0.615** | 0.509*** | 0.614*** | 0.614*** |
| | (0.245) | (0.187) | (0.165) | (0.193) |
| Within 13-24 months of 3 deadliest shootings | 0.774*** | 0.951*** | 0.771*** | 0.771*** |
| | (0.196) | (0.158) | (0.161) | (0.127) |
| Within 25-36 months of 3 deadliest shootings | 0.698*** | 0.885*** | 0.694*** | 0.694*** |
| | (0.178) | (0.171) | (0.174) | (0.176) |
| Within 37-48 months of 3 deadliest shootings | 0.262 | 0.430** | 0.258 | 0.258 |
| | (0.229) | (0.200) | (0.185) | (0.213) |
| Constant | 0.0982 | -1.747*** | -5.963*** | -5.963*** |
| | (0.258) | (0.242) | (1.037) | (0.275) |
| Pseudo R-squared | 0.115 | 0.127 | 0.0863 | - |
| Observations | 252 | 2,016 | 53,676 | 53,676 |
| No. geographical units | 1 | 7 | 213 | 213 |
| Standard error adjustment | Robust | Robust | Robust | State Cluster |
| Location fixed effects | | ✓ | ✓ | ✓ |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.18: Robust SE - Controlling for 3 Deadliest Shootings II

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Geographical unit | National | Regional | County | County |
| Dependent variable | No. Shootings | No. Shootings | No. Shootings | No. Shootings |
| Unemployment | 0.0356 | 0.0350 | 0.0357 | 0.0357* |
| | (0.0427) | (0.0368) | (0.0279) | (0.0217) |
| Summer | -1.157*** | -1.150*** | -1.156*** | -1.156*** |
| | (0.192) | (0.183) | (0.175) | (0.140) |
| Luby | 0.598*** | 0.615*** | 0.599*** | 0.599*** |
| | (0.167) | (0.145) | (0.143) | (0.128) |
| Virginia Tech | 0.653*** | 0.662*** | 0.651*** | 0.651*** |
| | (0.201) | (0.167) | (0.142) | (0.162) |
| Sandy Hook | 0.691** | 0.706*** | 0.688*** | 0.688*** |
| | (0.297) | (0.226) | (0.210) | (0.249) |
| Constant | 0.00742 | -1.897*** | -6.156*** | 6.156*** |
| | (0.269) | (0.243) | (1.030) | (0.272) |
| Pseudo R-squared | 0.108 | 0.122 | 0.0812 | - |
| Observations | 288 | 2,016 | 61,344 | 61,344 |
| No. geographical units | 1 | 7 | 213 | 213 |
| Standard error adjustment | Robust | Robust | Robust | State Cluster |
| Location fixed effects | | ✓ | ✓ | ✓ |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.19: Zero-Inflated Poission Regression

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Geographical unit | National | | Regional | |
| Dependent variable | No. Shootings | Inflate | No. Shootings | Inflate |
| Unemployment | 0.0754** | -0.265 | 0.0912** | -0.0565 |
| | (0.0332) | (0.222) | (0.0378) | (0.140) |
| Summer | -1.166*** | -0.0570 | -1.297*** | -0.954 |
| | (0.387) | (2.574) | (0.240) | (1.510) |
| Constant | 0.149 | -0.187 | -1.974*** | -14.85 |
| | (0.232) | (1.329) | (0.265) | (1,287) |
| Observations | 288 | 288 | 2,016 | 2,016 |
| No. geographical units | 1 | 1 | 7 | 7 |
| No. zero observations | 107 | 107 | 1700 | 1700 |
| Vuong test statistic | 1.471* | 1.471* | 1.426* | 1.426* |
| Location fixed effects | | | ✓ | ✓ |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.20: Zero-Inflated Poission Regression with Sub-period Intercepts

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Geographical unit | National | | Regional | |
| Dependent variable | No. Shootings | Inflate | No. Shootings | Inflate |
| Unemployment | -0.0917** | -0.964 | 0.0110 | 1.026* |
| | (0.0464) | (0.707) | (0.0427) | (0.529) |
| Summer | -1.032*** | 1.081 | -1.092*** | 0.0393 |
| | (0.189) | (1.213) | (0.201) | (0.993) |
| 1992-1994 | 1.571*** | -17.10 | 1.101*** | -4.539* |
| | (0.457) | (2,340) | (0.375) | (2.429) |
| 1994-2007 | 0.409 | -14.42 | 0.350 | -1.112 |
| | (0.457) | (580.0) | (0.353) | (1.117) |
| 2007-2013 | 1.340*** | -1.366 | 0.614* | -23.09 |
| | (0.442) | (1.509) | (0.355) | (2,148) |
| Constant | 0.258 | 5.278 | -1.999*** | -22.13 |
| | (0.549) | (4.377) | (0.445) | (1,543) |
| Observations | 288 | 288 | 2,016 | 2,016 |
| No. geographical units | 1 | 1 | 7 | 7 |
| No. zero observations | 107 | 107 | 1700 | 1700 |
| Vuong test statistic | 1.461* | 1.461* | 2.716*** | 2.716*** |
| Location fixed effects | | | ✓ | ✓ |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.21: Canada: Baseline Poisson Regression

| | (1) | (2) |
|---|---|---|
| | Canada | Canada |
| Sample | 1955-2017 | 1976-2015 |
| | No. school shootings | No. school shootings |
| Unemployment | 0.0237 | -0.429 |
| | (0.129) | (0.266) |
| Quarter 2 | 0.288 | 1.083 |
| | (0.764) | (1.155) |
| Quarter 3 | 0.304 | 1.374 |
| | (0.764) | (1.118) |
| Quarter 4 | 0.303 | 1.080 |
| | (0.764) | (1.155) |
| Constant | -3.216*** | -0.316 |
| | (1.108) | (2.240) |
| Observations | 250 | 160 |
| Pseudo R-squared | 0.00228 | 0.0648 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.22: Correlation of Unemployment and School Violence, 1992-2014

| | |
|---|---|
| **School-associated violent deaths of all persons (includes students, staff, and other nonstudents)** | |
| Total | -0.27 |
| School-associated - homicides | -0.37 |
| School-associated - suicides | 0.18 |
| Legal interventions | 0.16 |
| Unintentional firearm related deaths | -0.22 |
| Undetermined violent deaths | 0.05 |
| Homicides at school of youth ages 5-18 at school | -0.30 |
| Ratio of homicidies at school to total homicides of youth ages 5-18 at school | -0.04 |
| Suicides at school of youth ages 5-18 | -0.25 |
| Ratio of suicides at school to total suicides of youth ages 5-18 | -0.26 |
| | |
| **No. nonfatal victimizations against students ages 12-18 at school** | |
| Total | -0.27 |
| Theft | -0.26 |
| All violent | -0.27 |
| Serious violent | -0.21 |
| | |
| **Rate of victimization per 1000 students at school** | |
| Total | -0.21 |
| Theft | -0.21 |
| All violent | -0.21 |
| Serious violent | -0.17 |
| | |
| **No. nonfatal victimizations against students ages 12-18 away from school** | |
| Total | -0.29 |
| Theft | -0.29 |
| All violent | -0.29 |
| Serious violent | -0.25 |
| | |
| **Rate of victimization per 1000 students away from school** | |
| Total | -0.24 |
| Theft | -0.24 |
| All violent | -0.24 |
| Serious violent | -0.19 |

# Appendix C

# Appendix: Sentimental Business Cycles

## C.1 Data

Table C.1: Mass Shootings With 10 or More Fatalities

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

Table C.2: F tests for Alternative Confidence Indices

| Instrument | Mass Fatalities Coefficient | IV exclusion F- statistic |
|---|---|---|
| **Mother Jones Fatalities** | | |
| ICS | -1.12*** | 8.80 |
| ICE | -1.66*** | 11.16 |
| BUS5 | -1.57*** | 4.55 |
| BUS12 | -0.94** | 5.99 |
| PEXP | -0.24** | 3.74 |
| **Duwe Fatalities** | | |
| ICS | -0.74** | 5.41 |
| ICE | -1.02** | 5.87 |
| BUS5 | -0.84 | 1.90 |
| BUS12 | -0.46 | 2.00 |
| PEXP | -0.10 | 0.89 |

Figure C.1: Consumer Confidence vs. Industrial Production

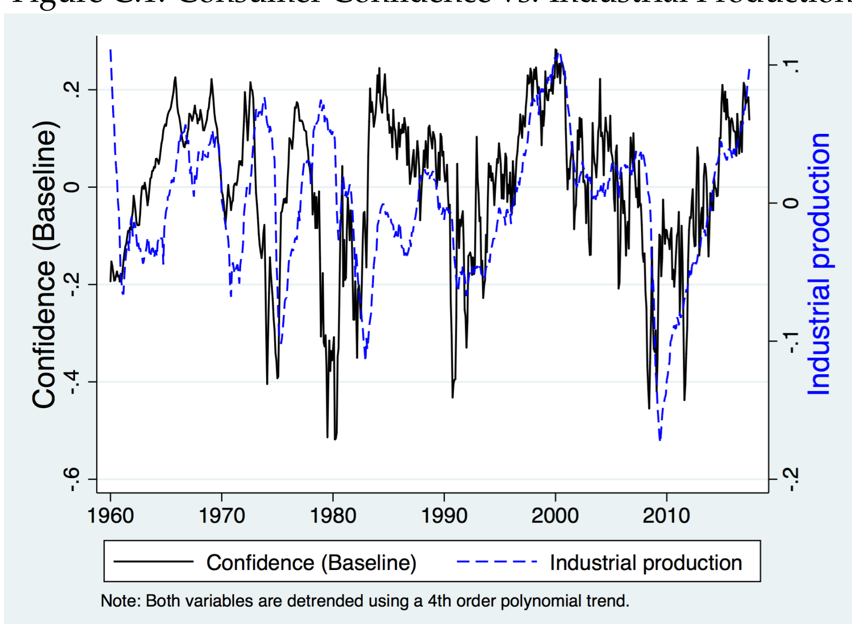


Figure C.2: Consumer Confidence vs. Unemployment

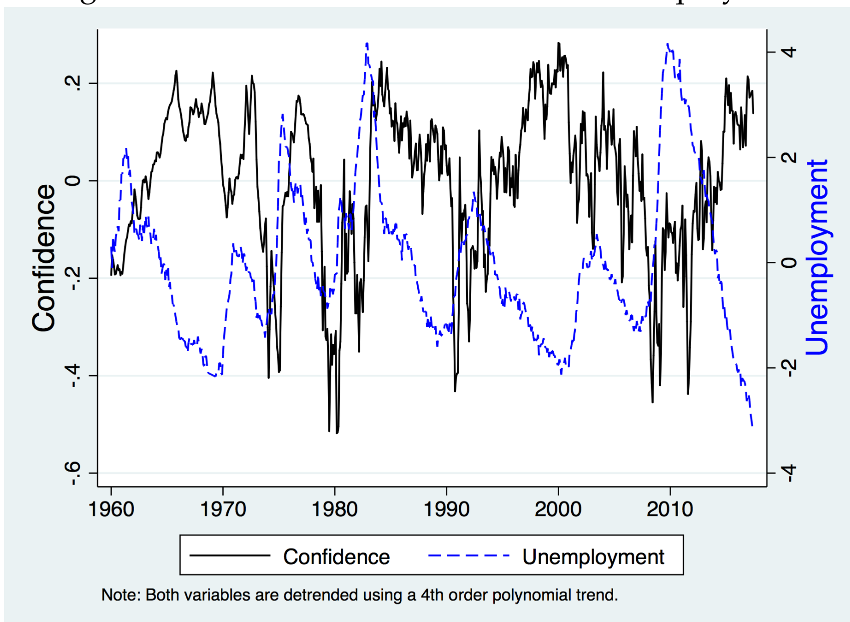



Figure C.3: Timeline of Mass Shootings and Fatalities

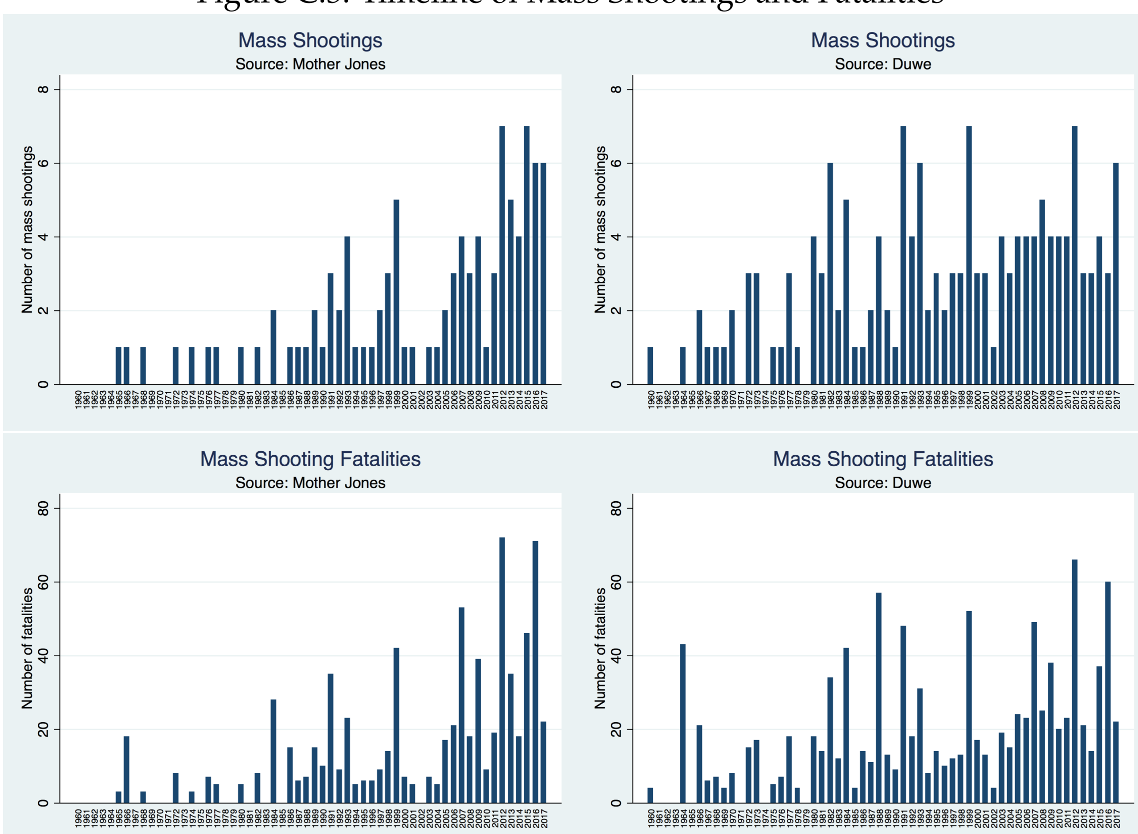


Table C.3: Exogeneity of Mass Shootings

| | (1) | (2) |
|---|---|---|
| Model | Poisson | Probit |
| | No. Mass Shootings | Mass Shooting Dummy |
| Unemployment rate | -5.6e4 | 0.003 |
| | (0.064) | (0.008) |
| Constant | -1.948 | |
| | (0.400) | |
| Observations | 690 | 690 |
| R-squared | 0.0005 | 0.0003 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## C.2 VAR Impulse Responses

Figure C.4: Consumer Sentiment Shock IRF - Benchmark

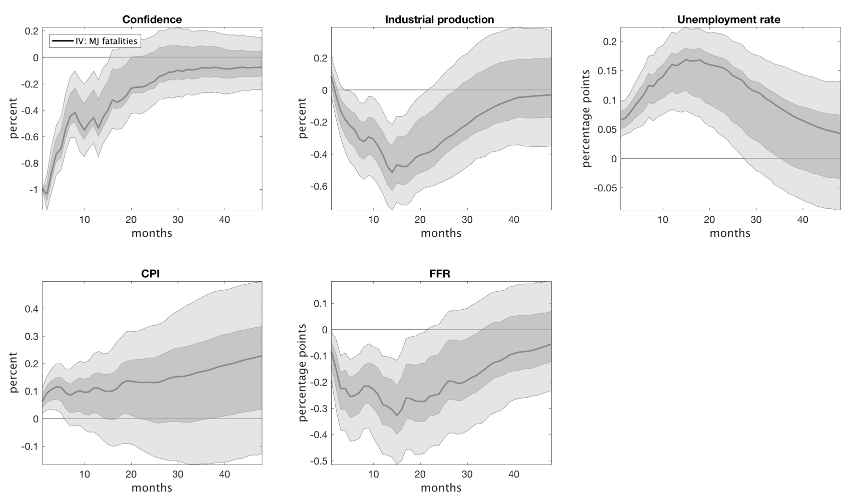


Figure C.5: Consumer Sentiment Shock IRF - Gertler-Karadi Cummulative Monetary Policy Shock

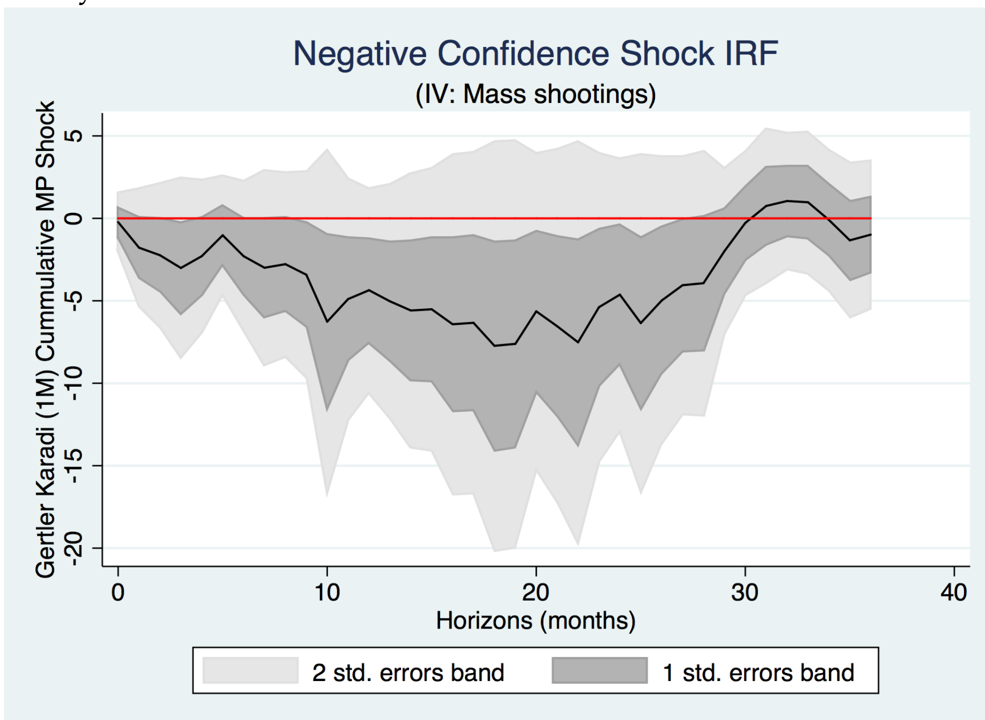



Figure C.6: Consumer Sentiment Shock IRF - Consumption

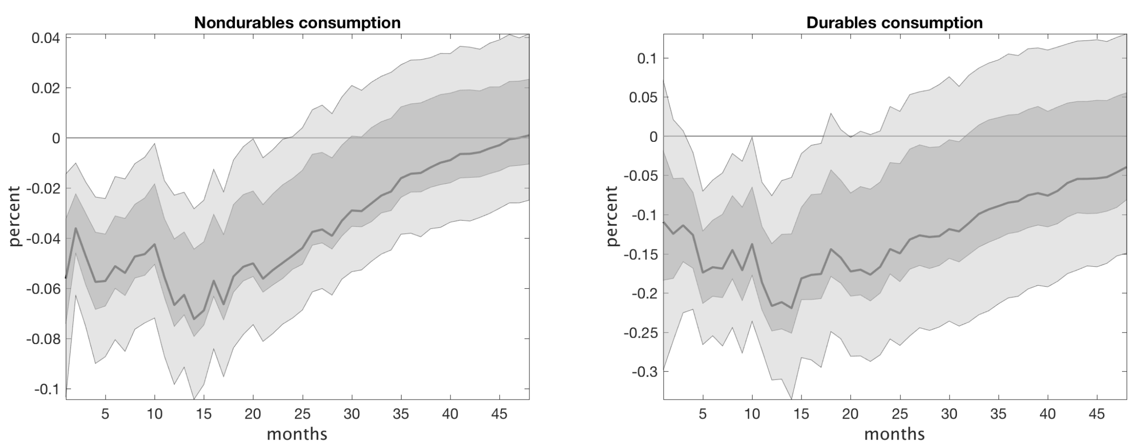


Figure C.7: Consumer Sentiment Shock IRF - Input Variables

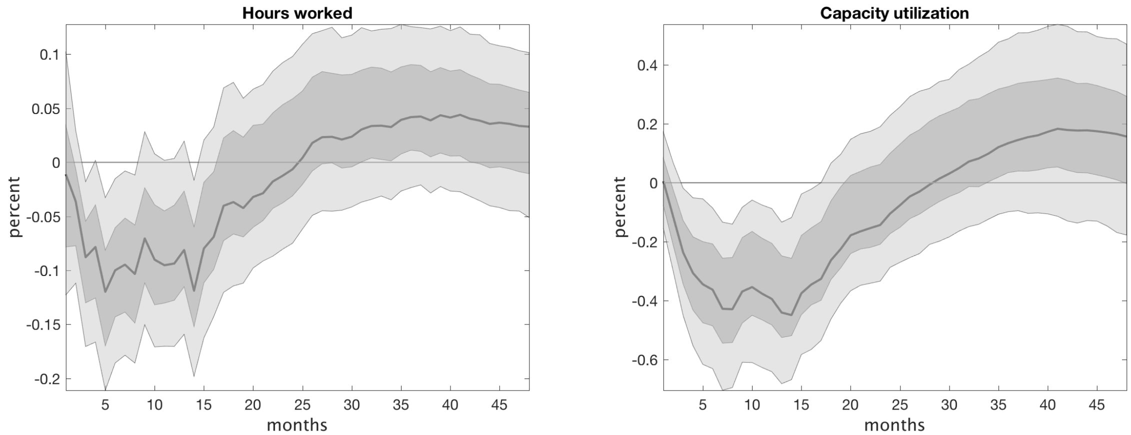



Figure C.8: Consumer Sentiment Shock IRF - Labor Market Tightness

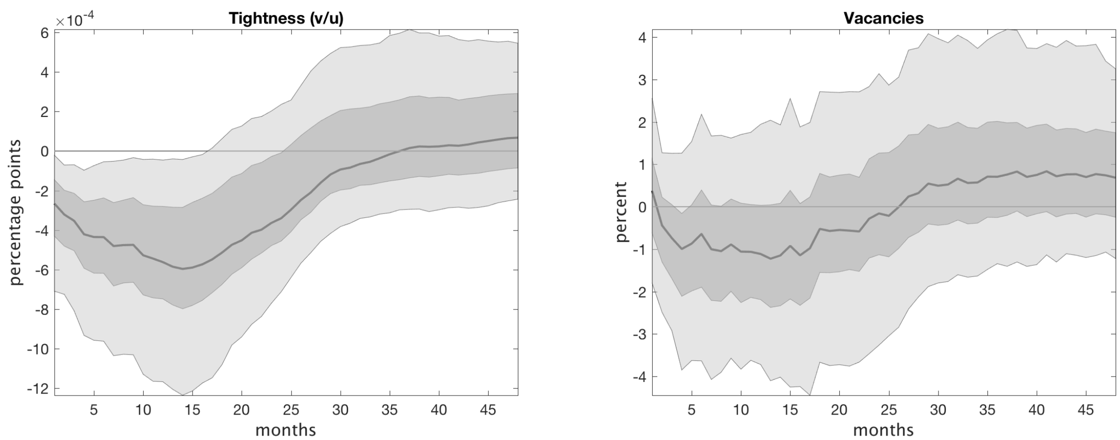



Figure C.9: Consumer Sentiment Shock IRF - Savings

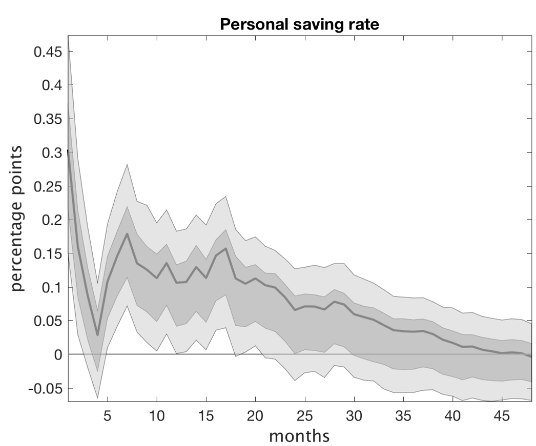


Figure C.10: Consumer Sentiment Shock IRF - Long-Term Interest Rates

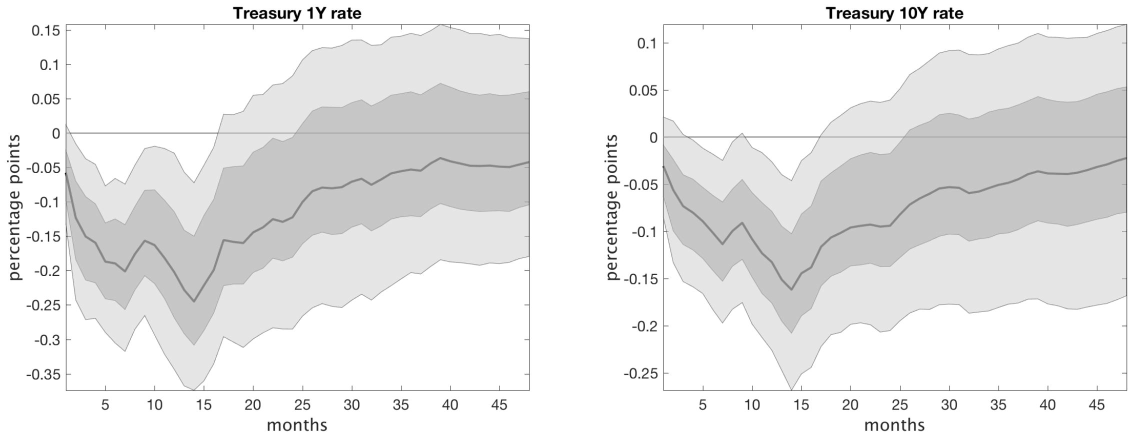



Figure C.11: Consumer Sentiment Shock IRF - Corporate Bond Spreads

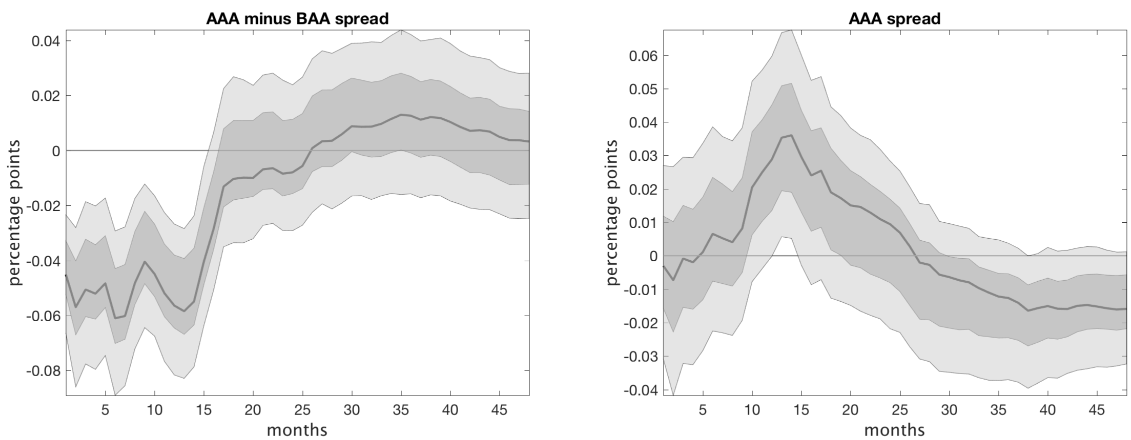



Figure C.12: Consumer Sentiment Shock IRF - Asset Prices

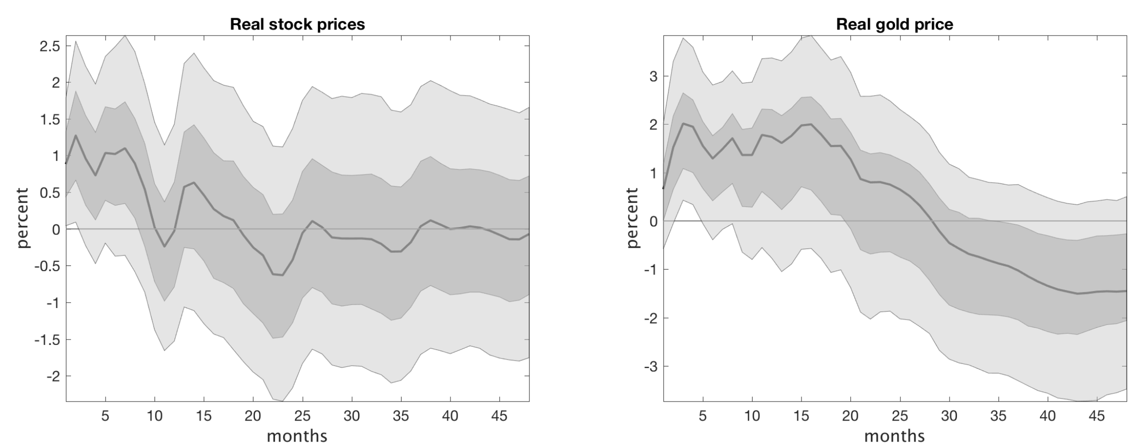


Figure C.13: Consumer Sentiment Shock IRF - Total Factor Productivity

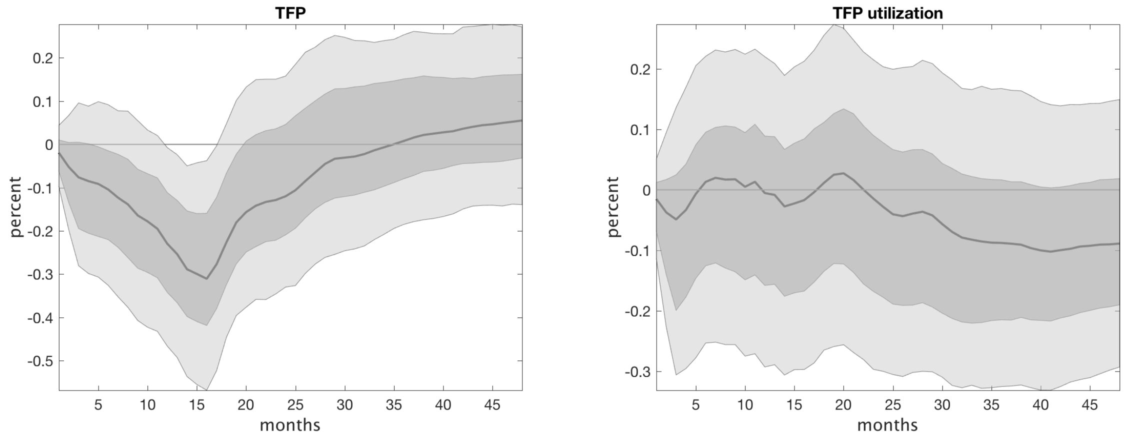



Figure C.14: Consumer Sentiment Shock IRF - Uncertainty

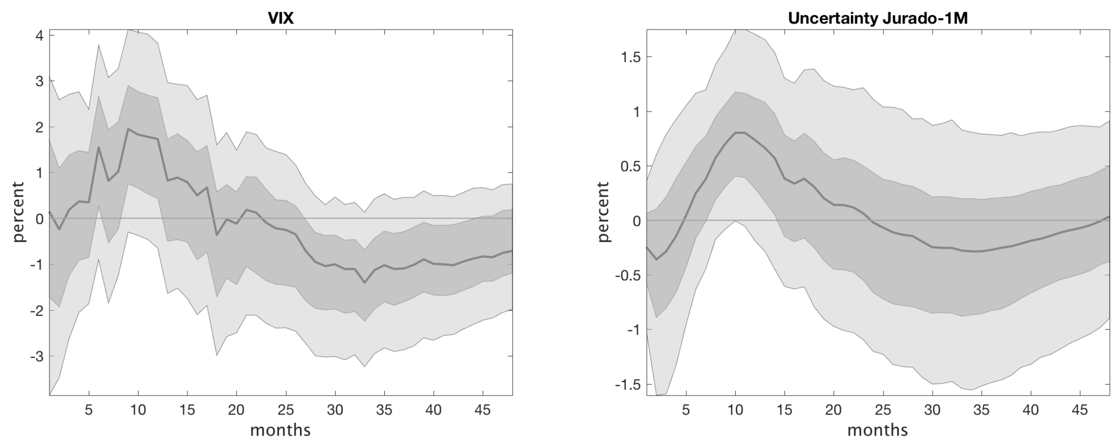


Figure C.15: Choleski SVAR Augmented with Adjusted TFP

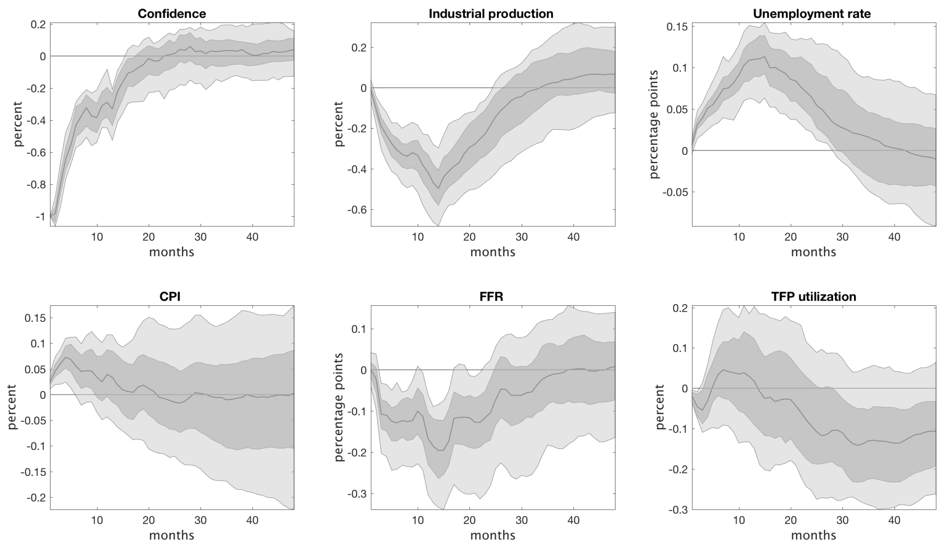



Figure C.16: Choleski SVAR Augmented with Jurado's Uncertainty Index

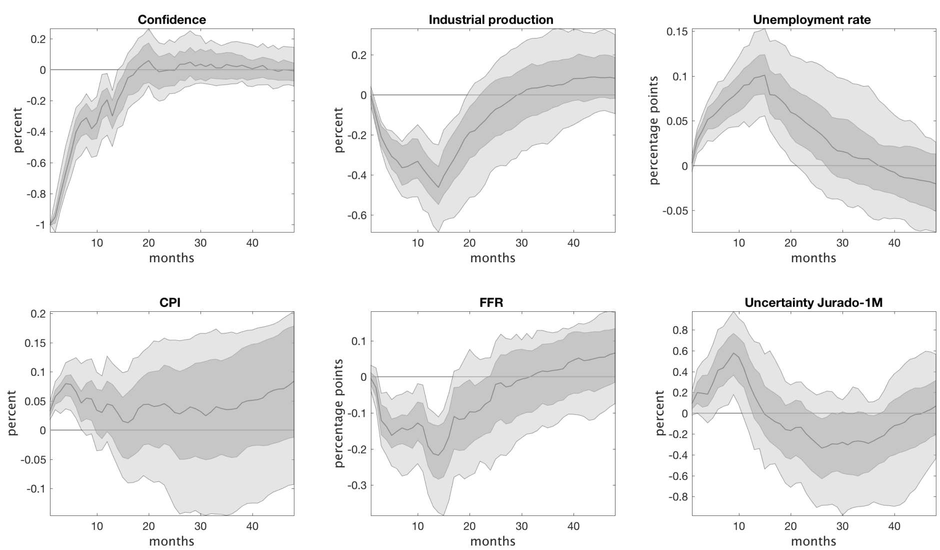
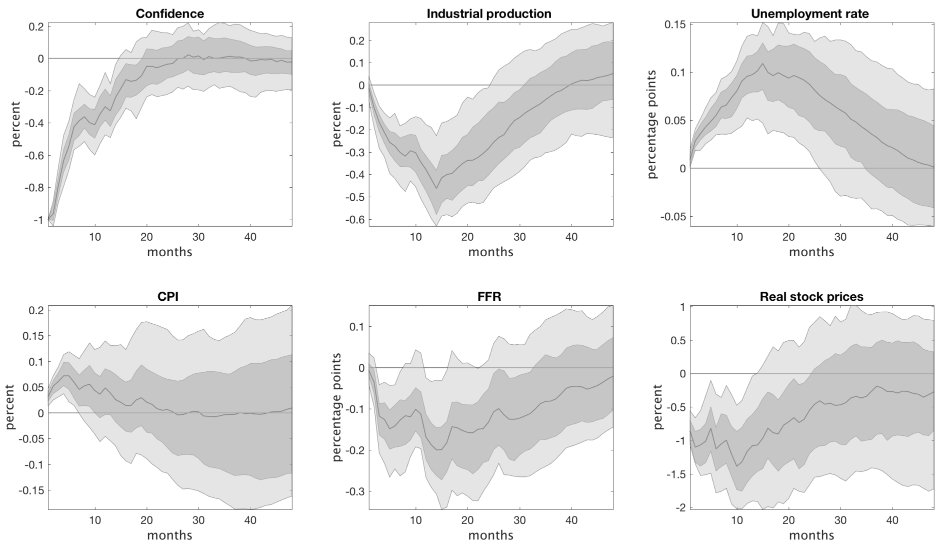


Figure C.17: Choleski SVAR Augmented with Real Stock Prices




## C.3 VAR Robustness

Figure C.18: Instrument Robustness - Duwe Dataset of Mass Shootings

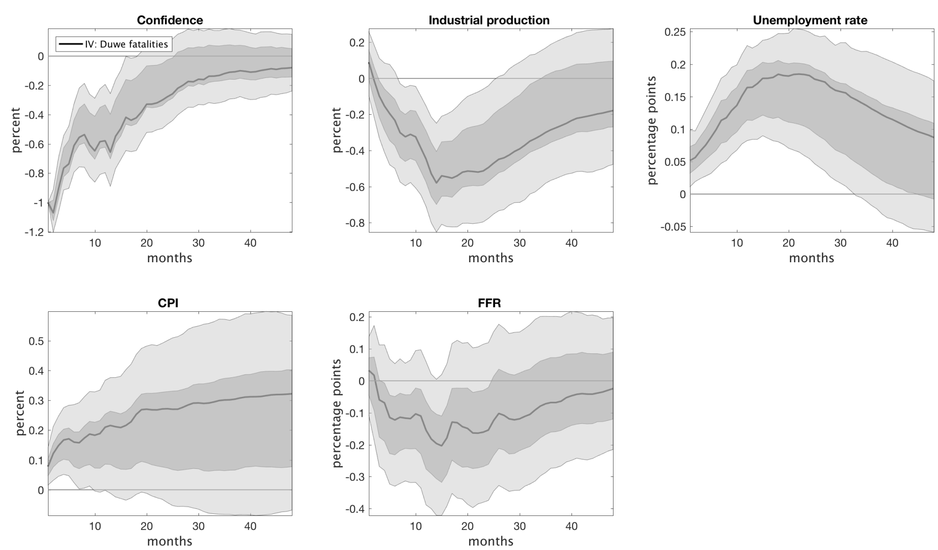


Figure C.19: Instrument Robustness - 10 Deadliest Mass Shootings

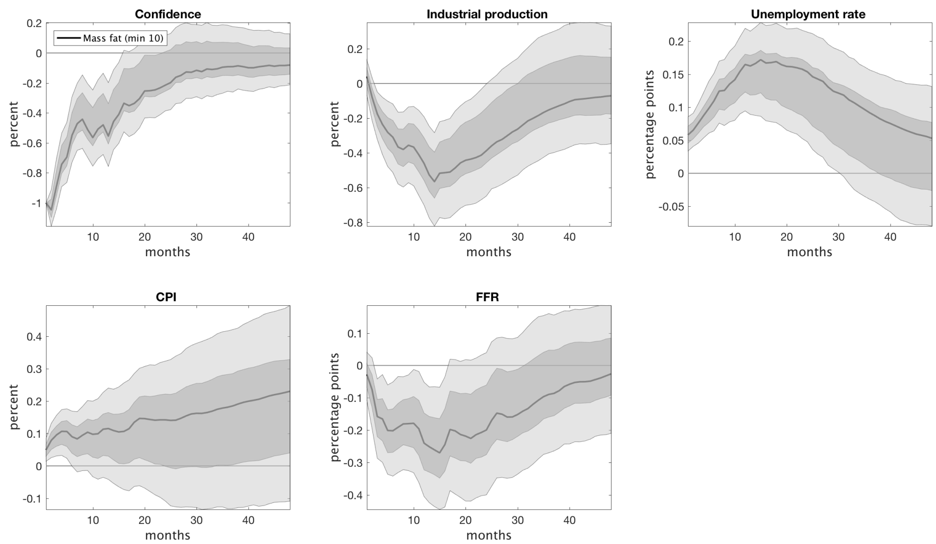



Figure C.20: Instrument Robustness - Media Coverage

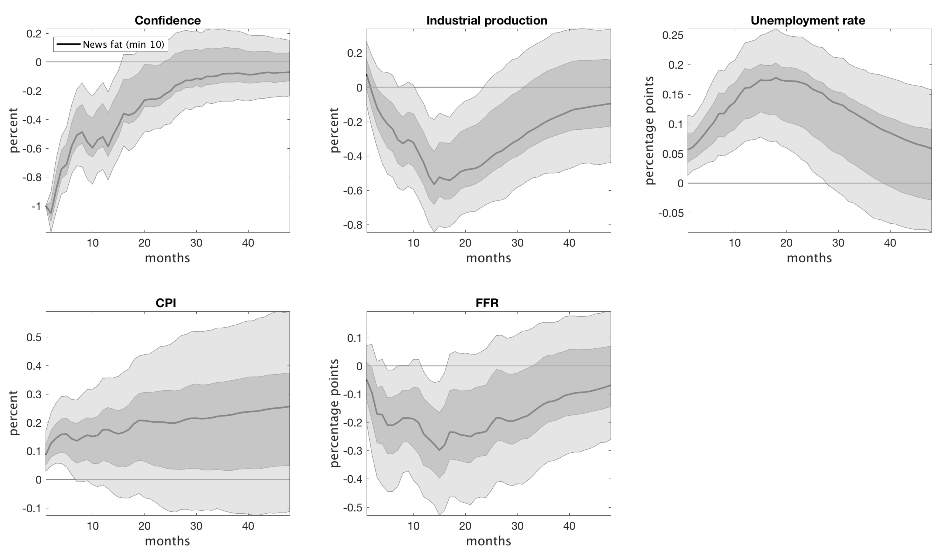


Figure C.21: Instrument Robustness - Detrended Mass Shootings

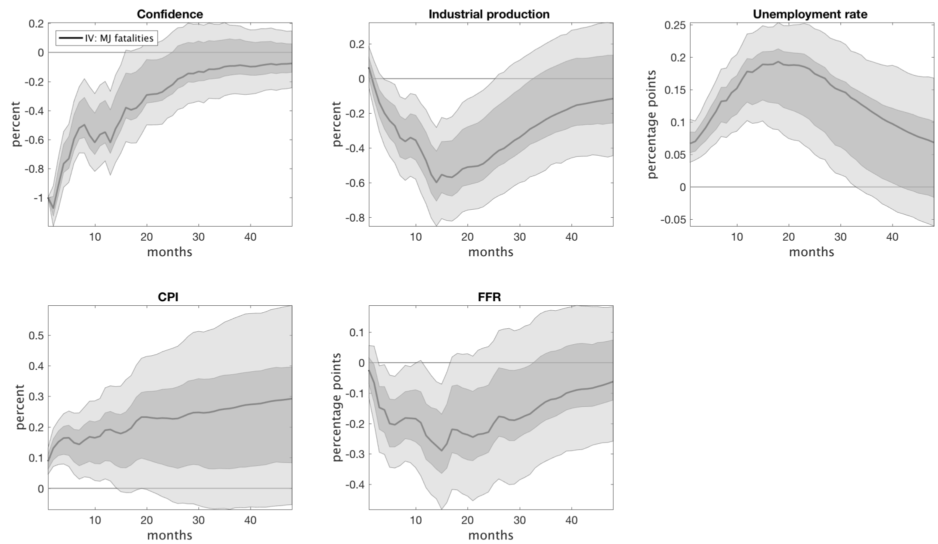



Figure C.22: Instrument Robustness - Number of Mass Shootings

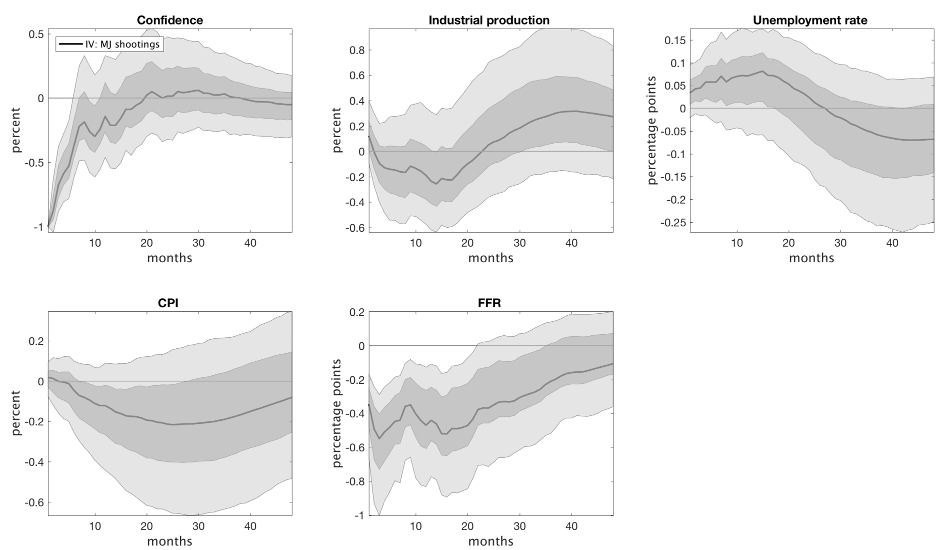
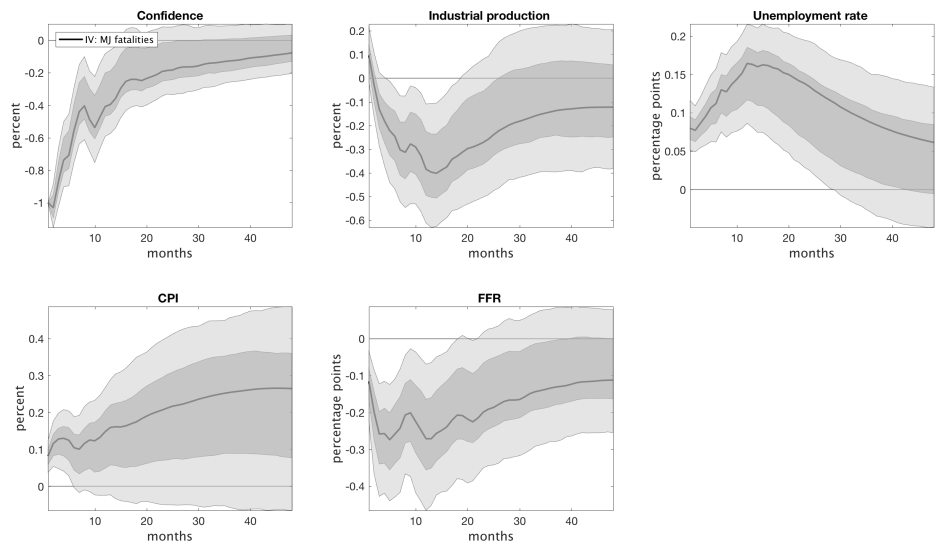


Figure C.23: Robustness - VAR with 12 Lags




## C.4 Model Impulse Responses

Figure C.24: Model IRFs - Monetary Policy Not Reacting to Sentiment Shock

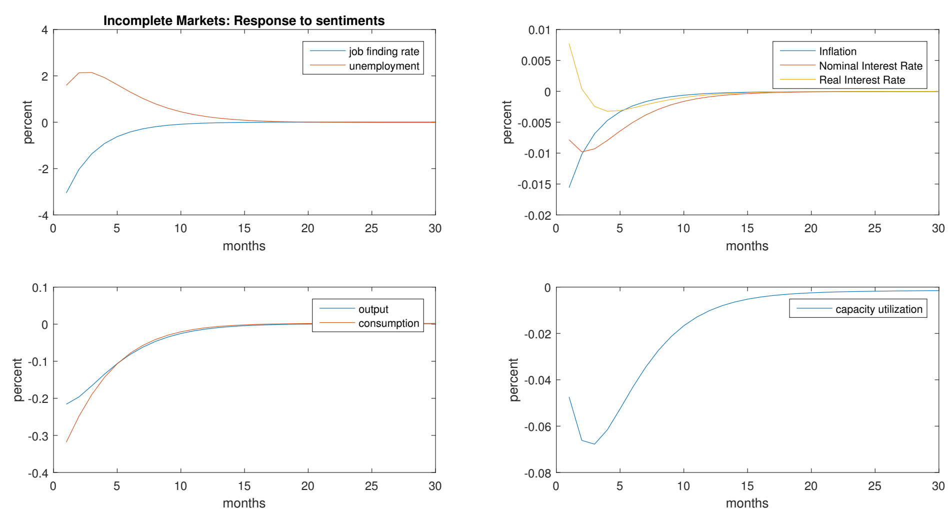
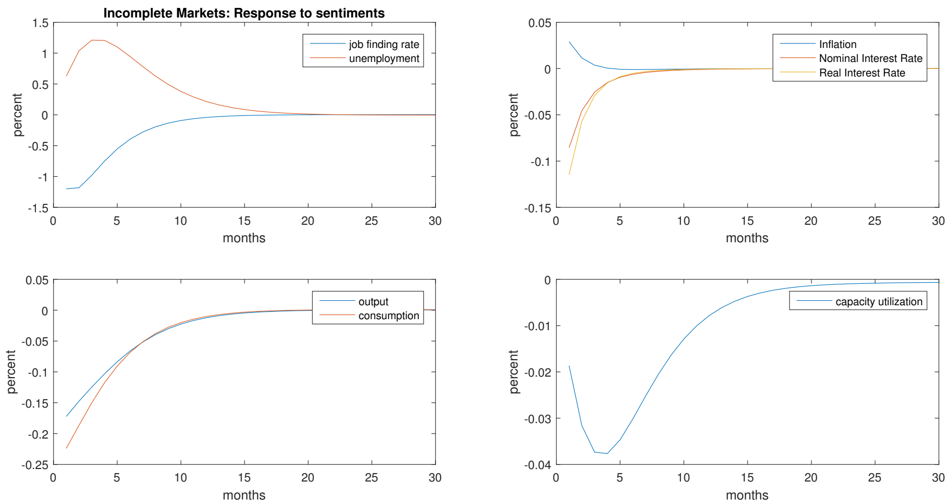


Figure C.25: Model IRFs - Monetary Policy Reacting to Sentiment Shock



# Appendix D

# Do Stock Market Booms Anticipate Baby Booms?

## D.1 Data

Figure D.1: Fertility in Response to the Global Financial Crisis

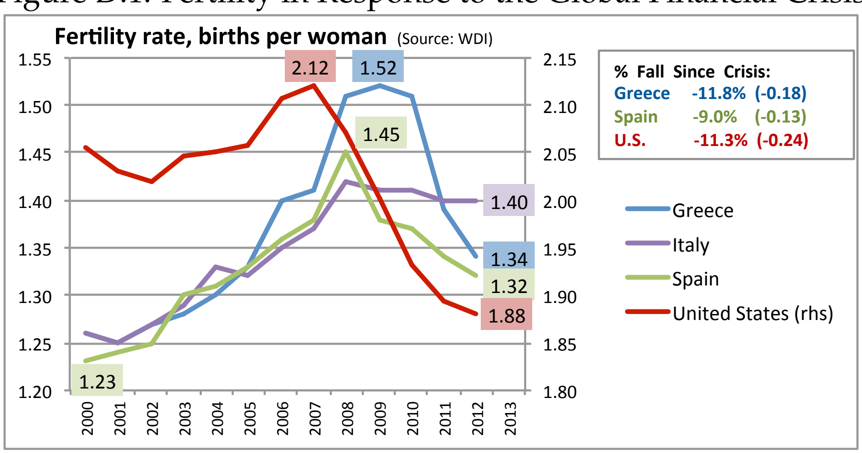


Figure D.2: Data on Fertility and Unemployment

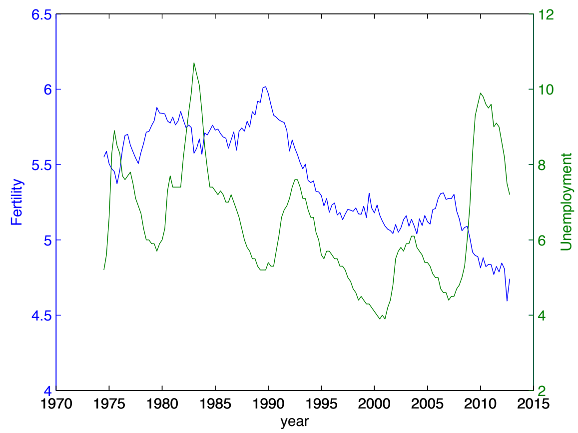
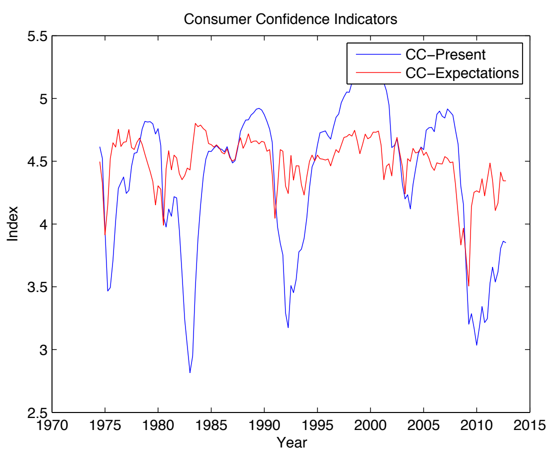
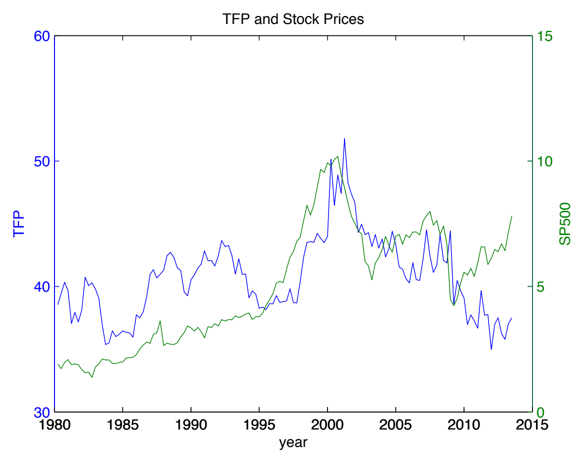



Figure D.3: Data on Consumer Confidence, TFP, and Stock Prices



## D.2 VAR Impulse Responses

Figure D.4: Positive Unemployment Shock

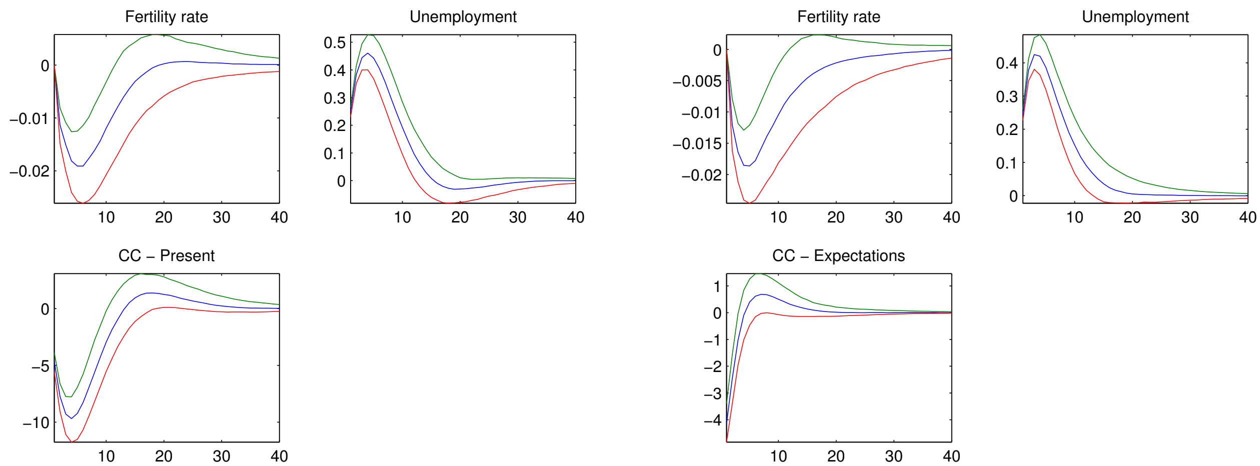



Figure D.5: Positive Consumer Confidence Shock: Present Situation (left panel) Expectations (right panel)

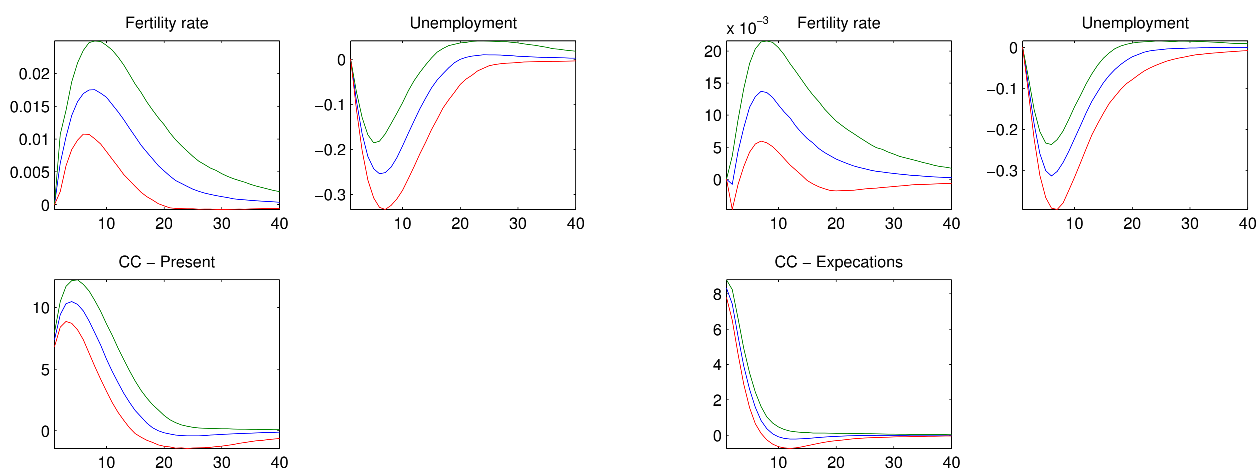


Figure D.6: Proxy VAR: Negative Confidence Shock

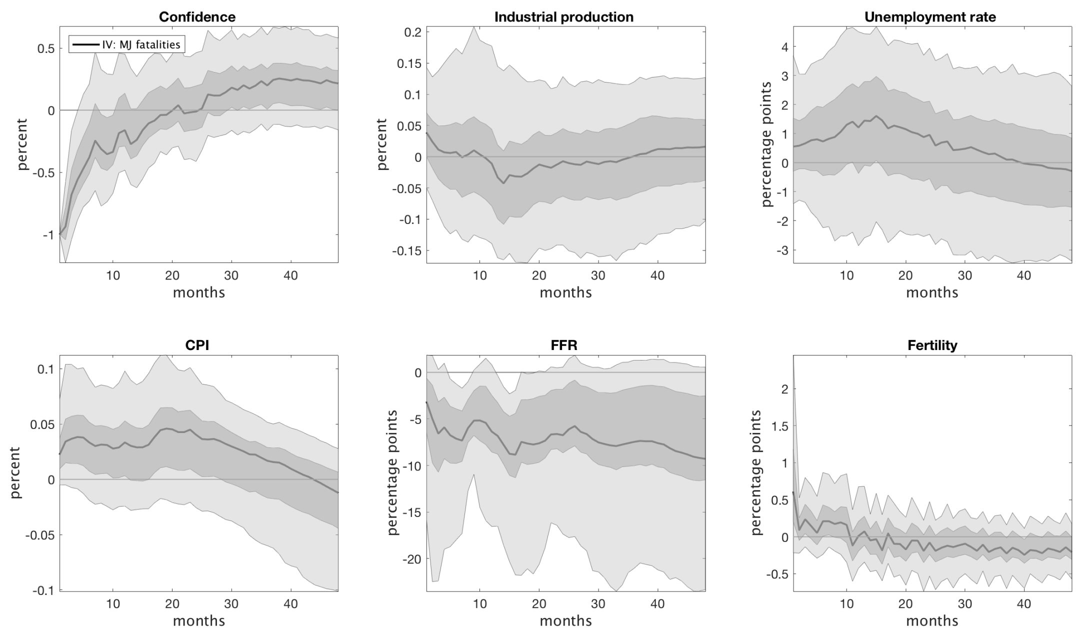
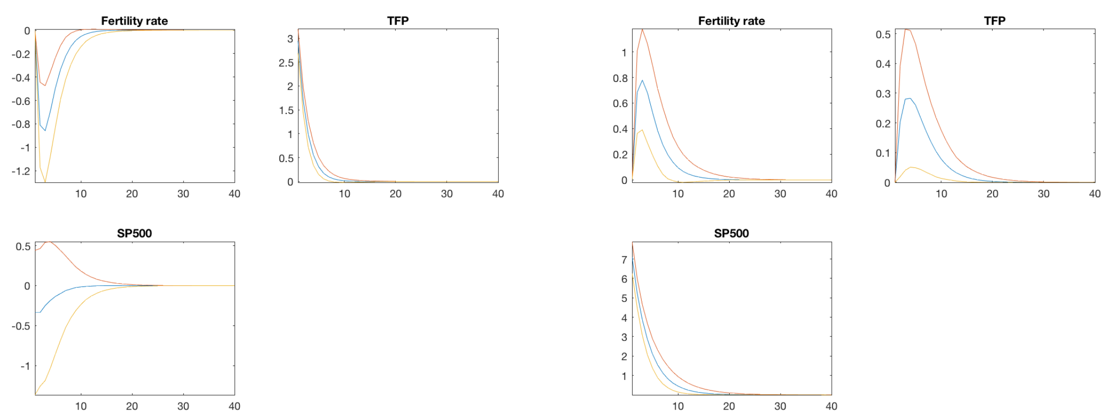



Figure D.7: Positive TFP Shock (left) and Stock Price News Shock (right)



## D.3 Model

Table D.1: Parameter Values

| **Parameter** | **Value** | **Description** | **Source** |
|---|---|---|---|
| $\beta$ | 0.98 | Time discount factor | Cooley and Prescott (1995) |
| $\alpha$ | 0.3 | Share of capital in production | Standard capital-income ratio |
| $\delta$ | 0.03 | Capital depreciation rate | Annual depreciation rate of 11.5% |
| $\rho$ | 0.65 | Elasticity of substitution | Doepke et al. (2007) |
| $\theta$ | 0.43 | Weight of female labor in production | Gender wage gap $\left(w^M/w^F\right) = 1.15$ |
| $\phi_c$ | 0.06 | Consumption cost of children (level) | Cost per child = 15% of parental income |
| $\psi_l$ | 0.5 | Time cost of children (curvature) | Doepke et al. (2007) |
| $\phi_l$ | 0.09 | Time cost of children (level) | 3 daily female hours for 2 children |
| $\delta_n$ | 0.025 | Children's depreciation | 10 years average childhood duration |
| $\eta$ | -3 | Utility of leisure elasticity parameter | Procyclicality of fertility |
| $\sigma_l$ | 0.35 | Utility weight on leisure | Female daily work hours = 5.3 |
| $\sigma_n$ | 0.465 | Utility weight on children | Implied value |
| $\rho_A$ | 0.9 | Persistence of technology | Cooley and Prescott (1995) |
| $\sigma_A$ | 0.1 | Standard deviation of technology shocks | Cooley and Prescott (1995) |

Table D.2: Steady State

| Variable | Value | Description |
|---|---|---|
| $n$ | 2.0 | Number of children |
| $h^F$ | 0.22 | Hours worked by female |
| $h$ | 0.28 | Hours worked by couple |
| $l^F$ | 0.65 | Hours of leisure for female |
| $w^F$ | 0.71 | Female wages |
| $w^M$ | 0.81 | Male wages |
| $y$ | 0.61 | Output |
| $c$ | 0.37 | Consumption |
| $k$ | 3.62 | Capital stock |
| $r$ | 0.05 | Interest rate |
| $A$ | 1 | Technology |

Figure D.8: Model IRFs to a "Transitory" TFP Shock

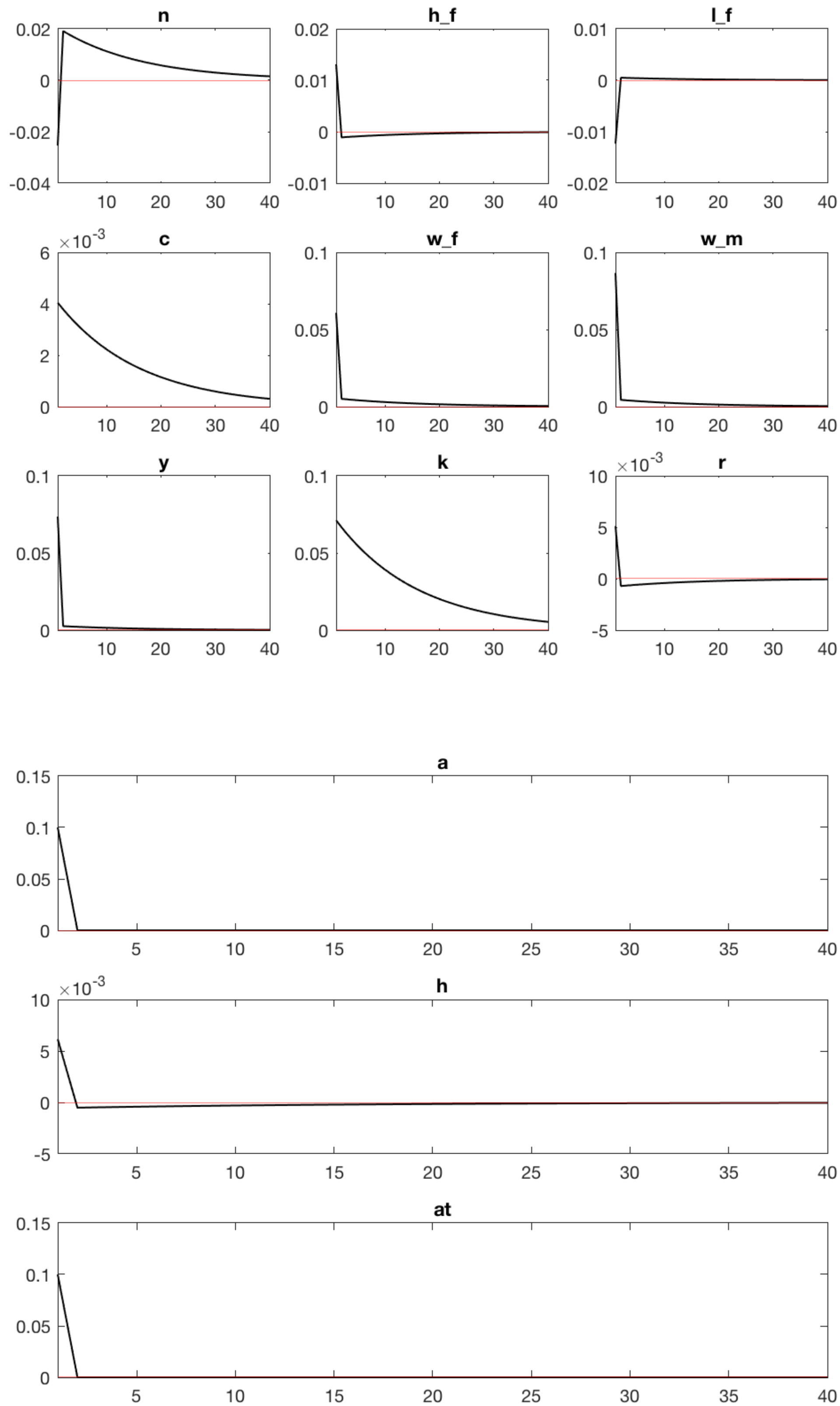


Figure D.9: Model IRFs to a "Persistent" TFP Shock

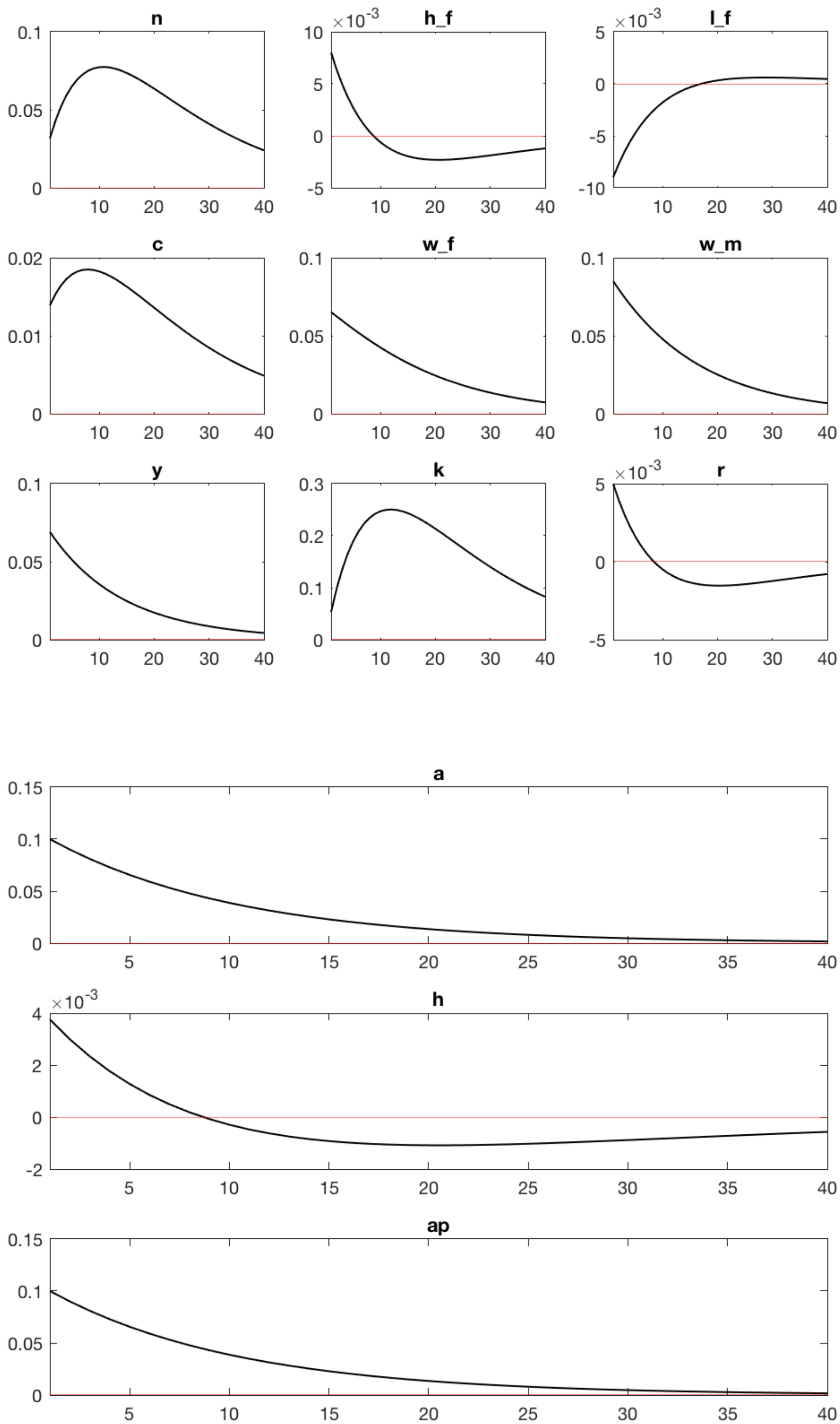


Figure D.10: Model IRFs to a News Shock

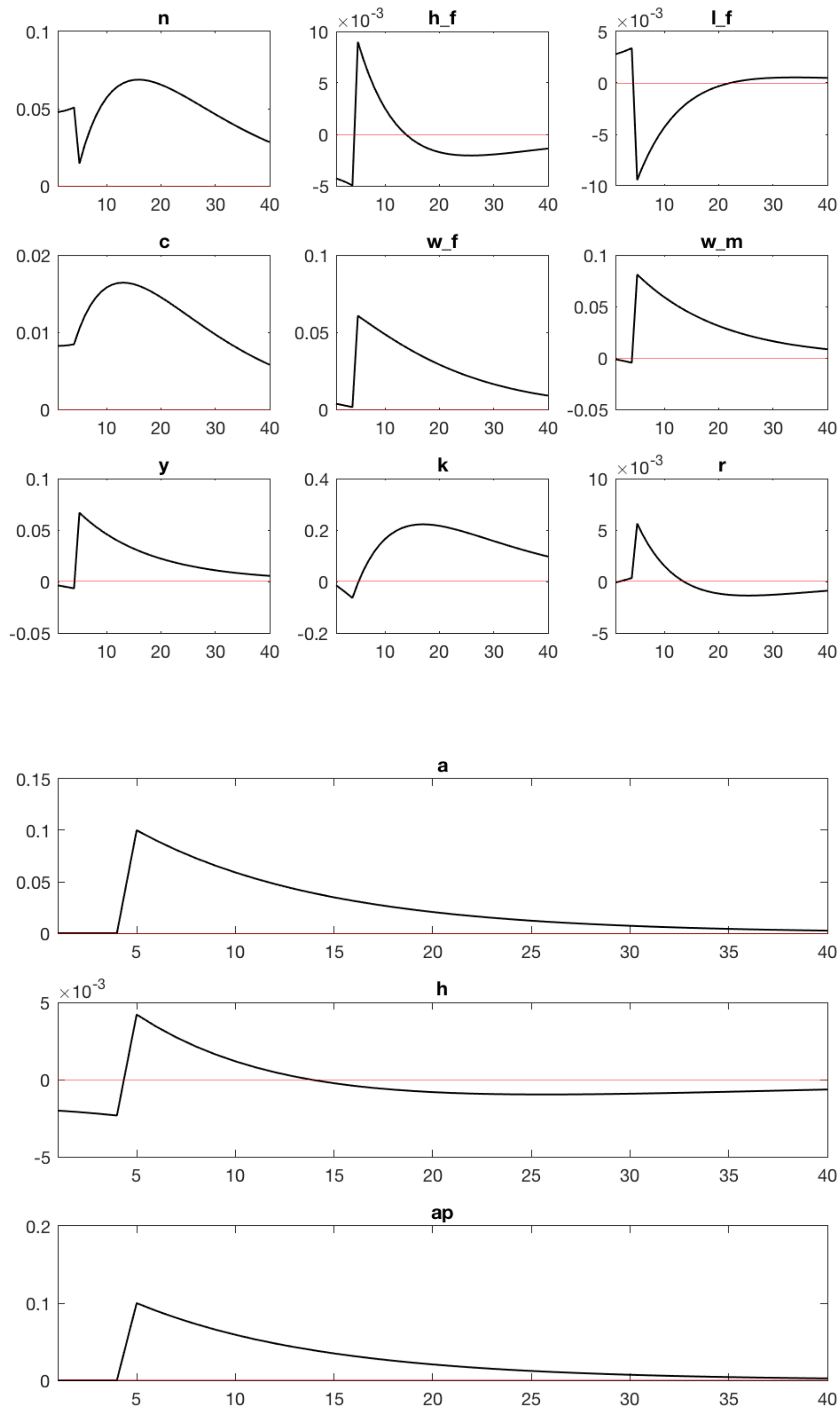


Figure D.11: Model IRFs to a Transitory TFP Shock (High Child Cost)

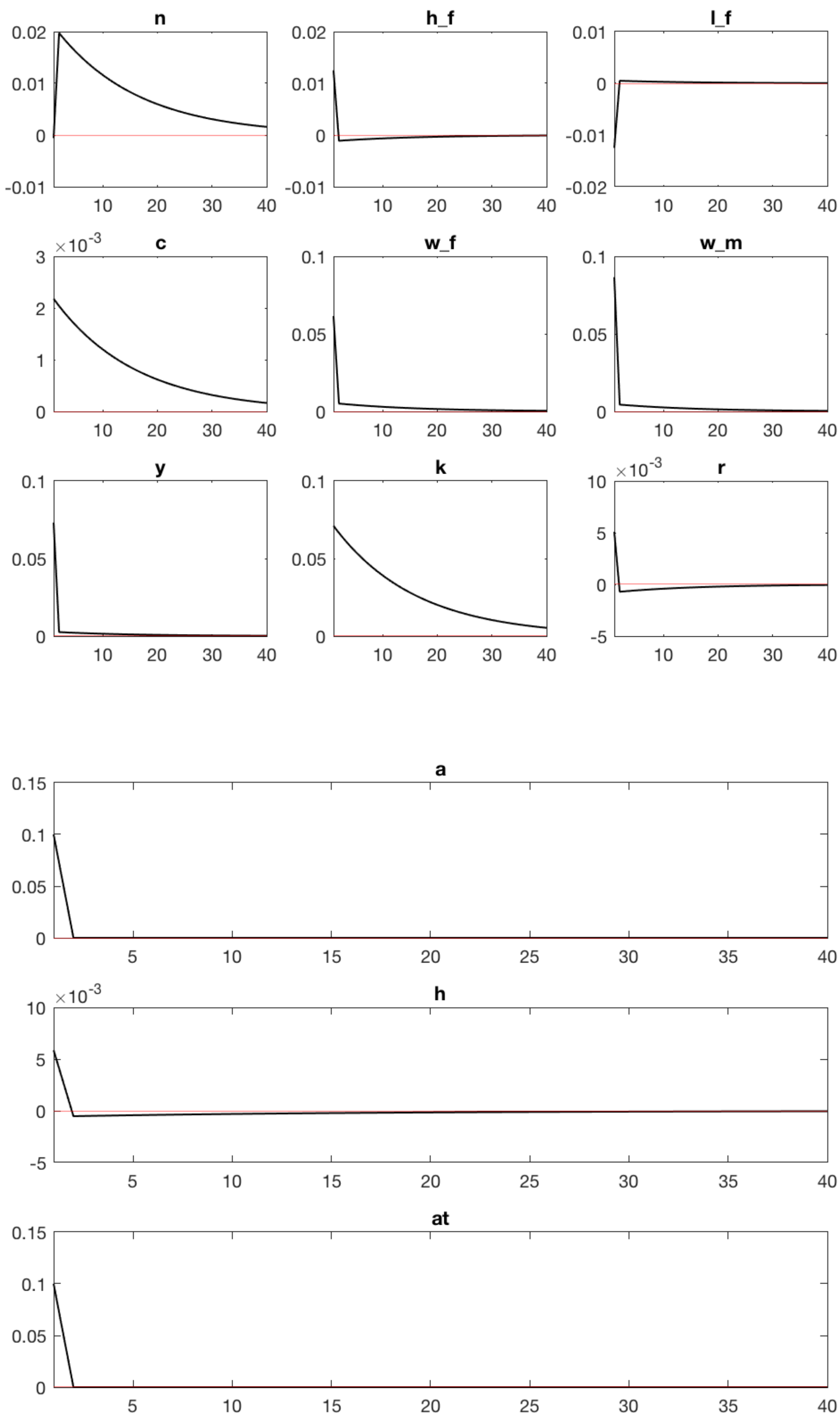


Figure D.12: Model IRFs to a Transitory TFP Shock (Low Child Cost)

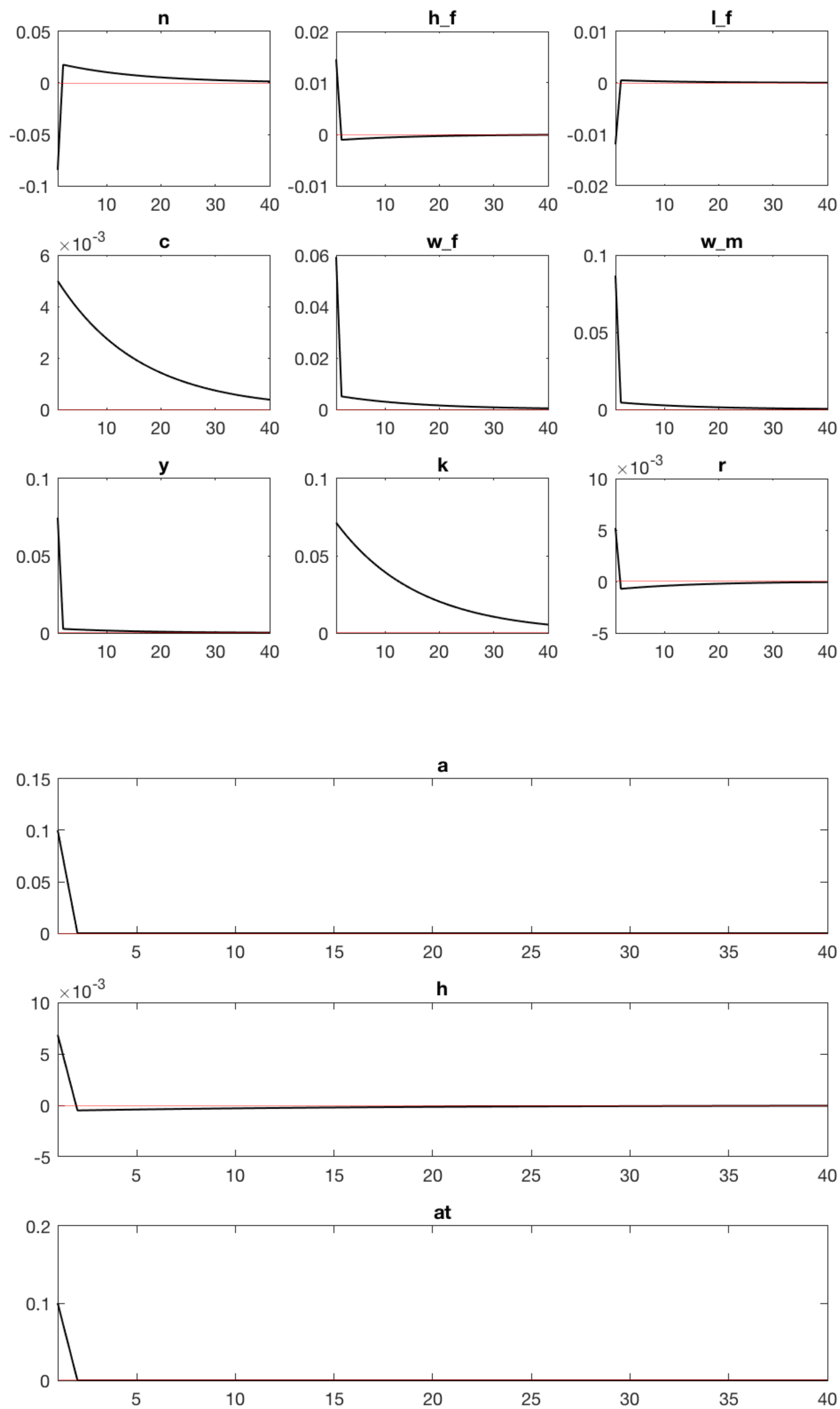


Figure D.13: Model IRFs to a Transitory TFP Shock (Log-Leisure)

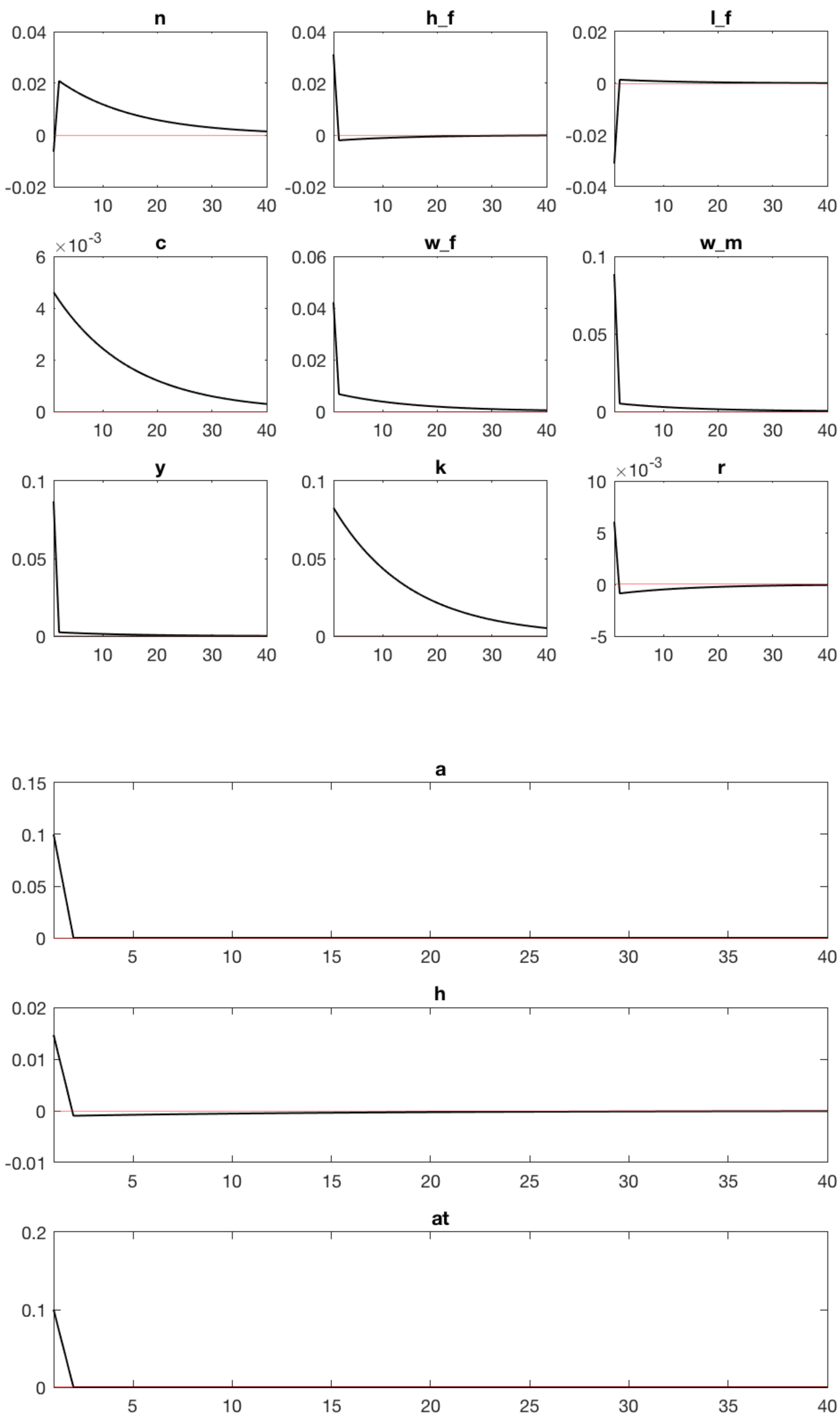
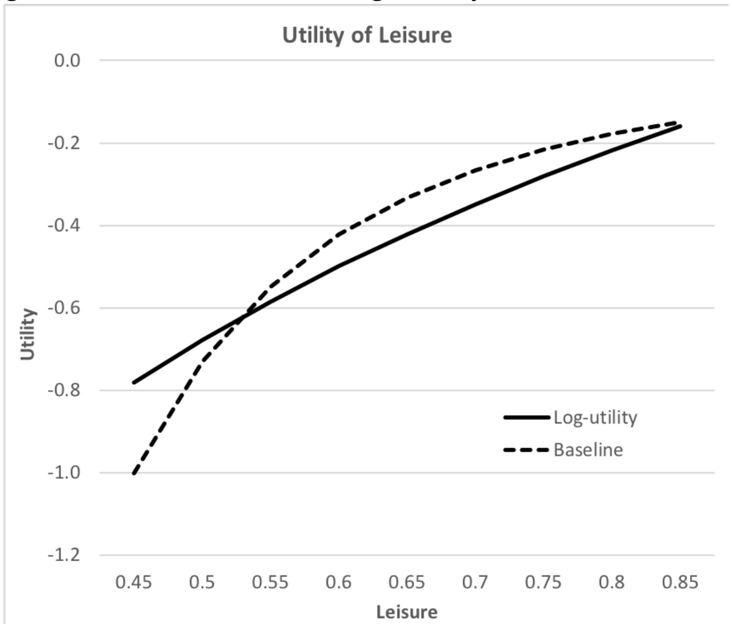
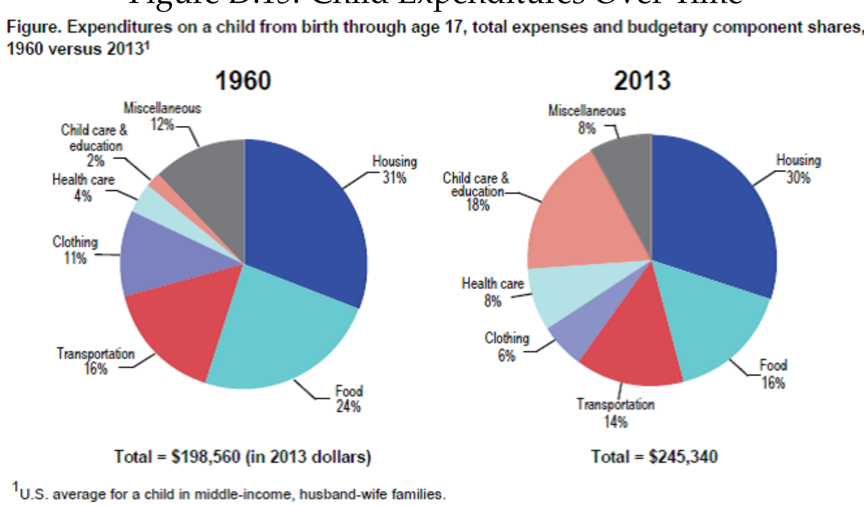


Figure D.14: Baseline vs. Log-Utility of Female Leisure




## D.4 Anecdotal Evidence on Fertility

Figure D.15: Child Expenditures Over Time



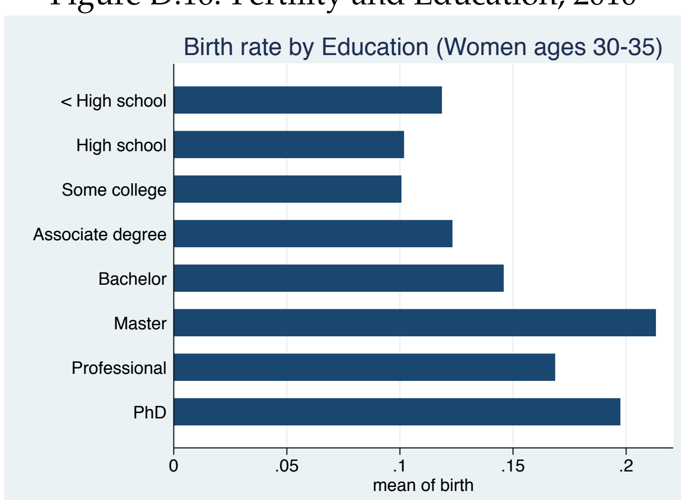

Source: USDA

Table D.3: Fertility by Age, Education, and Income

| | (1) Birth rate | (2) Birth rate | (3) Birth rate |
|---|---|---|---|
| Age | 0.028*** | 0.026*** | 0.025*** |
| | (0.001) | (0.001) | (0.001) |
| Age-Squared | -0.001*** | -0.001*** | -0.001*** |
| | (0.000) | (0.000) | (0.000) |
| Married | 0.098*** | 0.124*** | 0.124*** |
| | (0.001) | (0.003) | (0.003) |
| Education | -0.022*** | | -0.014*** |
| | (0.002) | | (0.004) |
| Education-Squared | 0.001*** | | 0.001*** |
| | (0.000) | | (0.000) |
| Household income | | -0.000*** | -0.000*** |
| | | (0.000) | (0.000) |
| Household income-Squared | | 0.000*** | 0.000*** |
| | | (0.000) | (0.000) |
| Constant | -0.173*** | -0.214*** | -0.120*** |
| | (0.011) | (0.015) | (0.024) |
| Observations | 291,954 | 57,015 | 57,015 |
| R-squared | 0.058 | 0.066 | 0.067 |
| Fixed Effects | Year | Year | Year |

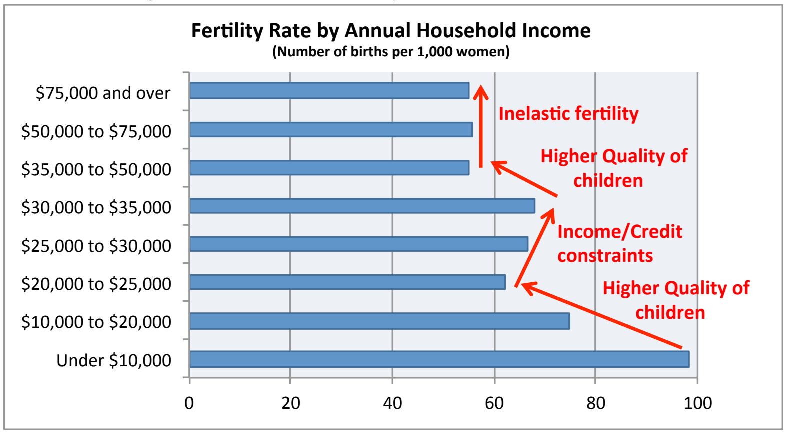
Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure D.16: Fertility and Education, 2010




Source: USDA

Figure D.17: Fertility and Income, 2012




Source: USDA

# D.5 County-level Evidence on Credit Constraints

## D.5.1 House Prices

Table D.4: Fertility Response to House Prices: White Women by Age Group

| VARIABLES | (1) Age 15-19 | (2) Age 20-24 | (3) Age 25-29 | (4) Age 30-34 | (5) Age 35-39 | (6) Age 40-44 |
|---|---|---|---|---|---|---|
| Ln(Personal inc pc) (-1) | 18.803*** | 25.859*** | 18.901*** | 14.386*** | 7.476*** | 0.108 |
| | (1.960) | (3.481) | (3.298) | (2.515) | (1.531) | (0.590) |
| Ln(House prices) (-1) | 2.390*** | 12.185*** | 8.160*** | 4.483*** | 0.991* | 0.385* |
| | (0.732) | (1.301) | (1.232) | (0.940) | (0.572) | (0.220) |
| Constant | -170.905*** | -232.619*** | -114.060*** | -71.252*** | -37.669** | 5.206 |
| | (19.088) | (33.903) | (32.116) | (24.492) | (14.915) | (5.743) |
| Observations | 4,539 | 4,540 | 4,540 | 4,540 | 4,540 | 4,515 |
| R-squared | 0.596 | 0.650 | 0.387 | 0.091 | 0.108 | 0.093 |
| Number of countycode | 454 | 454 | 454 | 454 | 454 | 454 |
| Fixed Effects | County-Year | County-Year | County-Year | County-Year | County-Year | County-Year |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table D.5: Fertility Response to House Prices: African American Women by Age Group

| VARIABLES | (1) Age 15-19 | (2) Age 20-24 | (3) Age 25-29 | (4) Age 30-34 | (5) Age 35-39 | (6) Age 40-44 |
|---|---|---|---|---|---|---|
| Ln(Personal inc pc) (-1) | 3.118 | -6.196 | -6.865 | 6.410 | -1.119 | -1.034 |
| | (4.956) | (9.730) | (9.264) | (6.976) | (4.053) | (1.494) |
| Ln(House prices) (-1) | -1.748 | 7.063* | 16.194*** | 9.112*** | 3.475** | -0.159 |
| | (1.876) | (3.631) | (3.507) | (2.641) | (1.487) | (0.524) |
| Constant | 42.020 | 161.047* | 100.747 | -40.117 | 30.868 | 20.411 |
| | (48.064) | (94.700) | (90.186) | (68.066) | (39.755) | (14.833) |
| Observations | 3,615 | 4,101 | 4,013 | 3,810 | 3,198 | 1,805 |
| R-squared | 0.475 | 0.266 | 0.035 | 0.062 | 0.064 | 0.072 |
| Number of countycode | 398 | 438 | 432 | 417 | 372 | 241 |
| Fixed Effects | County-Year | County-Year | County-Year | County-Year | County-Year | County-Year |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.6: Fertility Response to House Prices: Asian Women by Age Group

| VARIABLES | (1) Age 15-19 | (2) Age 20-24 | (3) Age 25-29 | (4) Age 30-34 | (5) Age 35-39 | (6) Age 40-44 |
|---|---|---|---|---|---|---|
| Ln(Personal inc pc) (-1) | -10.962 | 11.393 | 22.967* | -12.178 | -0.371 | 5.946* |
| | (9.071) | (10.996) | (12.075) | (10.960) | (7.320) | (3.401) |
| Ln(House prices) (-1) | 5.722** | 20.623*** | 12.891*** | 18.289*** | 3.333 | -2.584*** |
| | (2.302) | (3.711) | (4.391) | (3.925) | (2.555) | (0.987) |
| Constant | 115.215 | -149.129 | -181.355 | 154.771 | 52.803 | -33.610 |
| | (91.272) | (109.218) | (119.248) | (108.105) | (72.773) | (34.309) |
| Observations | 970 | 2,686 | 3,734 | 3,813 | 2,973 | 1,242 |
| R-squared | 0.244 | 0.139 | 0.048 | 0.016 | 0.013 | 0.013 |
| Number of countycode | 151 | 353 | 427 | 428 | 367 | 183 |
| Fixed Effects | County-Year | County-Year | County-Year | County-Year | County-Year | County-Year |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

### D.5.2 Household Debt

Table D.7: Fertility Response to Debt Burden: White Women by Age Group

| VARIABLES | (1) Age 15-19 | (2) Age 20-24 | (3) Age 25-29 | (4) Age 30-34 | (5) Age 35-39 | (6) Age 40-44 |
|---|---|---|---|---|---|---|
| Ln(Personal inc pc) (-1) | 15.247*** | 22.654*** | 23.345*** | 21.447*** | 12.150*** | 1.498 |
| | (3.269) | (5.718) | (6.681) | (5.082) | (3.330) | (1.305) |
| HH debt-to-income (-1) | -3.897*** | -6.298*** | -3.007** | -0.184 | 1.170* | -0.151 |
| | (0.668) | (1.169) | (1.366) | (1.039) | (0.681) | (0.266) |
| Constant | -116.878*** | -128.460** | -115.197* | -121.697** | -82.551** | -7.026 |
| | (34.122) | (59.682) | (69.734) | (53.046) | (34.755) | (13.619) |
| Observations | 1,816 | 1,816 | 1,816 | 1,816 | 1,816 | 1,806 |
| R-squared | 0.095 | 0.169 | 0.086 | 0.102 | 0.059 | 0.046 |
| Number of countycode | 454 | 454 | 454 | 454 | 454 | 454 |
| Fixed Effects | County-Year | County-Year | County-Year | County-Year | County-Year | County-Year |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.8: Fertility Response to Debt Burden: African American Women by Age Group

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Age 15-19 | Age 20-24 | Age 25-29 | Age 30-34 | Age 35-39 | Age 40-44 |
| Ln(Personal inc pc) (-1) | 21.350* | 15.173 | 2.355 | -0.329 | 0.368 | 2.296 |
| | (11.234) | (21.888) | (18.270) | (14.033) | (7.896) | (2.852) |
| HH debt-to-income (-1) | -4.102* | -15.537*** | -8.485** | -2.065 | -2.545 | -0.633 |
| | (2.403) | (4.580) | (3.884) | (2.940) | (1.735) | (0.622) |
| Constant | -152.096 | 1.176 | 100.948 | 81.118 | 37.537 | -13.714 |
| | (117.362) | (228.556) | (190.859) | (146.705) | (82.728) | (30.033) |
| Observations | 1,456 | 1,624 | 1,596 | 1,501 | 1,264 | 700 |
| R-squared | 0.021 | 0.030 | 0.029 | 0.050 | 0.023 | 0.010 |
| Number of countycode | 390 | 424 | 423 | 398 | 344 | 208 |
| Fixed Effects | County-Year | County-Year | County-Year | County-Year | County-Year | County-Year |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.9: Fertility Response to Debt Burden: Asian Women by Age Group

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Age 15-19 | Age 20-24 | Age 25-29 | Age 30-34 | Age 35-39 | Age 40-44 |
| Ln(Personal inc pc) (-1) | -3.803 | 7.697 | -0.426 | 9.499 | -9.057 | 0.077 |
| | (22.373) | (20.609) | (25.353) | (23.161) | (15.517) | (9.227) |
| HH debt-to-income (-1) | 3.056 | -8.505** | -8.711* | -5.909 | -5.558* | -0.295 |
| | (2.791) | (4.085) | (5.075) | (4.610) | (3.205) | (1.154) |
| Constant | 63.359 | 4.279 | 137.478 | 30.632 | 169.244 | 15.221 |
| | (234.113) | (215.795) | (265.277) | (242.348) | (163.007) | (97.526) |
| Observations | 415 | 1,090 | 1,482 | 1,500 | 1,168 | 459 |
| R-squared | 0.094 | 0.019 | 0.027 | 0.004 | 0.010 | 0.009 |
| Number of countycode | 135 | 326 | 404 | 406 | 332 | 145 |
| Fixed Effects | County-Year | County-Year | County-Year | County-Year | County-Year | County-Year |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

# Appendix E

# Appendix: Do Labor Market Institutions Matter for Fertility?

## E.1 Data Description

Figure E.1: TFR vs. Average Birth Rate

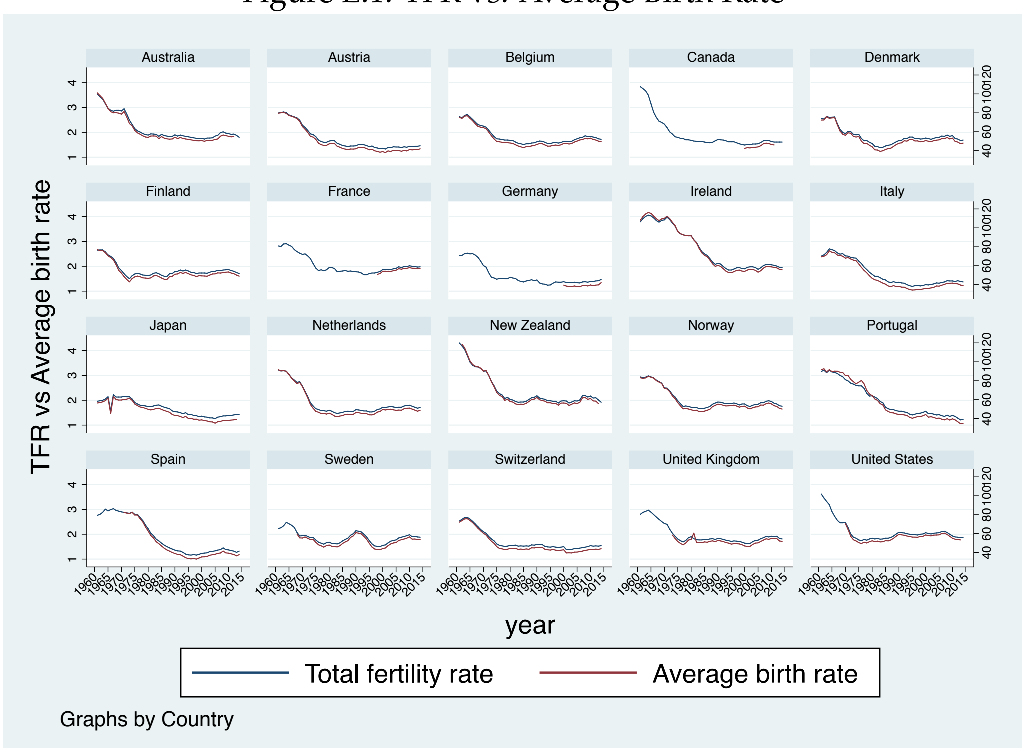


Figure E.2: Heterogeneity in Total Fertility Rates

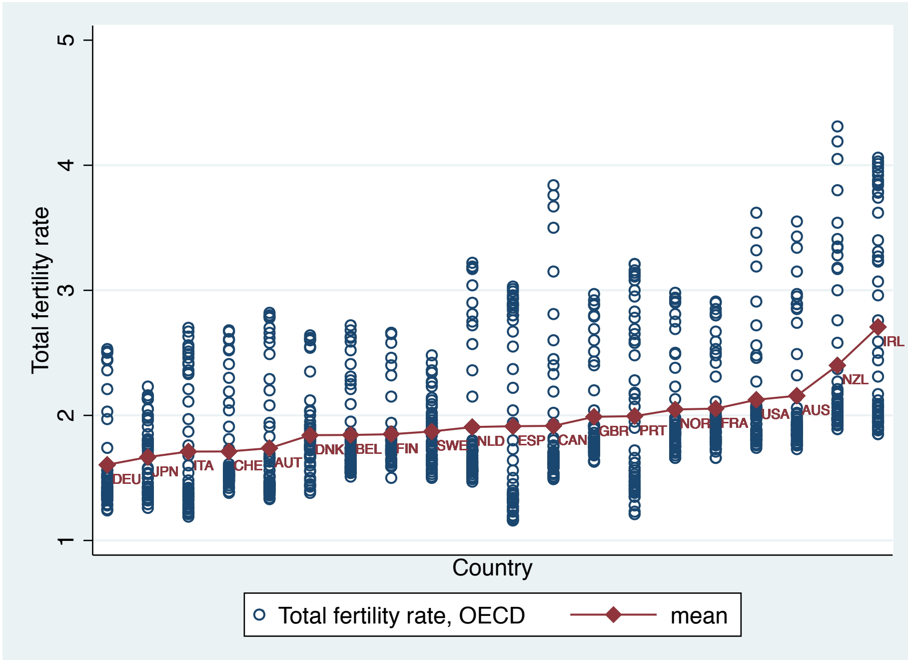



Figure E.3: Birth Rate, by Age Group

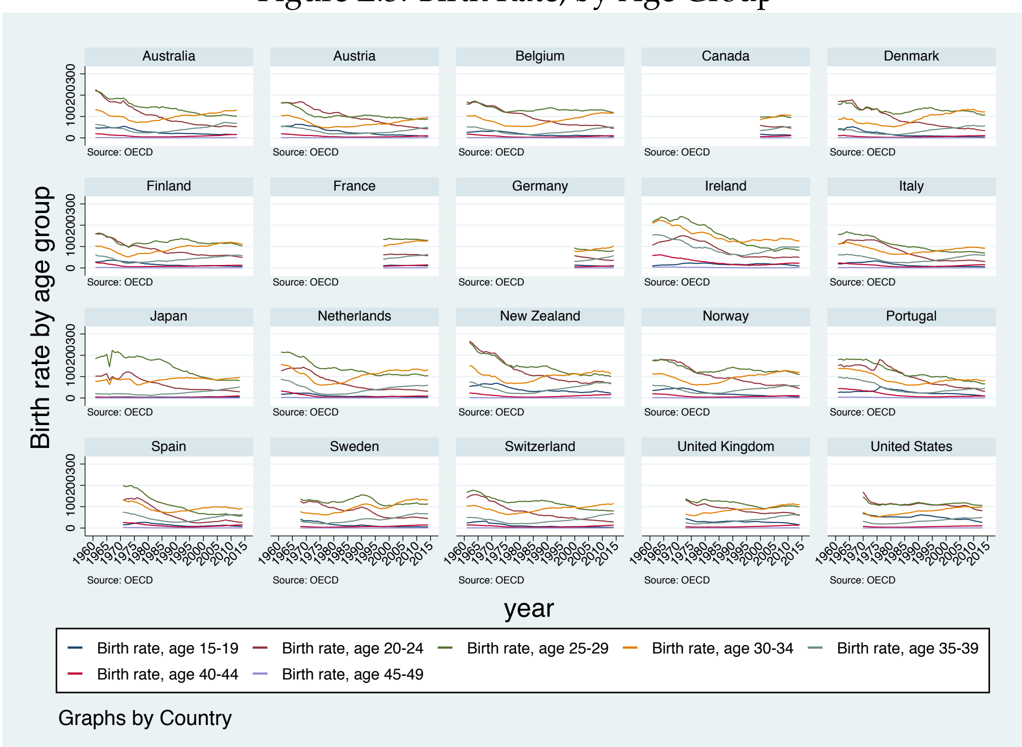


Table E.1: Description of Labor Market Institutions

| LMI | Description | Source |
|---|---|---|
| Employment protection for temporary contracts | Measures the strictness of regulation on the use of fixed-term and temporary work agency contracts. It is expressed in a 0-6 scale. | OECD |
| Employment protection for permanent contracts | Measures the strictness of regulation of individual dismissal of employees on regular/indefinite contracts. It is expressed in a 0-6 scale. | OECD |
| Union density | It represents the ratio of wage and salary earners that are trade union members, divided by the total number of wage and salary earners. It is constructed using both survey and administrative data. | OECD |
| Union coverage | This indicator refers to the percentage of workers covered by collective agreements normalized on employment. | CEP-OECD |
| Union concentration | Summary measure of concentration of unions at industry and sectoral level. It ranges between 0-1. | ITCWSS |
| Wage bargaining centralization | Summary measure of centralization of wage bargaining, taking into account both union authority and concentration at multiple levels. Derived from Iversen's centralization index, it ranges between 0-1. | ITCWSS |
| Government intervention in wage bargaining | Index of government intervention in the wage bargaining process. It spans between 1 and 5, where 1 means no intervention. | ITCWSS |
| Wage bargaining level | Index between 0 and 5, which indicates the predominant level where the wage bargaining takes place. e.g. firm level, industry, nation level. | ITCWSS |
| Extension of collective agreements | Mandatory extension of collective agreements to non-organized employers. It has a 0-3 scale, where 3 indicates that the extension is virtually automatic and more or less general. | ITCWSS |
| Minimum wage | Degree of government intervention and discretion in setting the minimum wage. It ranges between 0 and 8, where 0 indicates no minimum wage. | ITCWSS |
| Unemployment benefit | Benefit replacement rates, which indicates the average across the first five years of unemployment for three family situations and two money levels. | OECD |

Table E.2: Descriptive Statistics for Labor Market Institutions

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Employment protection (temp.) | 1080 | 1.9 | 1.46 | 0.25 | 5.25 |
| Employment protection (perm.) | 1080 | 2.1 | 1.0 | 0.3 | 5.0 |
| Union density | 1080 | 39.7 | 19.2 | 7.6 | 83.9 |
| Union coverage | 1080 | 69 | 25 | 7 | 99 |
| Wage bargaining centralization | 1080 | 0.40 | 0.18 | 0.08 | 0.98 |
| Union concentration | 1080 | 0.32 | 0.11 | 0.14 | 0.59 |
| Government intervention | 1080 | 2.7 | 1.3 | 1.0 | 5.0 |
| Level of wage bargaining | 1080 | 3.0 | 1.3 | 1.0 | 5.0 |
| Ext. of coll. agreements | 1080 | 1.4 | 1.3 | 0.0 | 3.0 |
| Minimum wage | 1080 | -3.9 | 3.0 | -8.0 | 0.0 |
| Unemployment benefit | 1080 | 26.1 | 13.6 | 0.0 | 65.2 |

Table E.3: Descriptive Statistics for Control Variables

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Family allowance, av. per child (USD) | 1080 | 105 | 76 | 0 | 433 |
| Maternity benefits | 1080 | 2165 | 2549 | 0 | 13363 |
| Female labor force participation | 1080 | 47.3 | 11.7 | 17.8 | 71.2 |
| Gender wage gap | 1080 | 38 | 22 | -11 | 119 |
| GDP growth | 1080 | 3.0 | 2.6 | -8.3 | 12.9 |
| Unemployment rate | 1080 | 5.8 | 4.1 | 0 | 26.1 |
| NAIRU | 1080 | 6.0 | 3.5 | 0.2 | 20.3 |

Table E.4: Correlation with Principal Components: LMIs

| | (1) EPL | (2) UnS | (3) WB | (4) UB |
|---|---|---|---|---|
| Employment protection (temp.) | 0.893*** | | | |
| Employment protection (perm.) | 0.893*** | | | |
| Union density | | 0.805*** | | |
| Union coverage | | 0.798*** | | |
| Union concentration | | 0.467*** | | |
| Wage bargaining centralization | | | 0.567*** | |
| Government intervention | | | 0.769*** | |
| Level of wage bargaining | | | 0.665*** | |
| Extension of collective agreements | | | 0.738*** | |
| Minimum wage | | | 0.0397 | |
| Unemployment benefit | | | | 1 |
| Observations | 1080 | 1080 | 1080 | 1080 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table E.5: Correlation with Principal Components: Controls

| | (1) PC maternity | (2) PC gender | (3) PC economy |
|---|---|---|---|
| Family allowance | 0.810*** | | |
| Maternity benefits | 0.812*** | | |
| Female labor force participation | | -0.818*** | |
| Gender wage gap | | 0.819*** | |
| GDP growth | | | 0.390*** |
| Unemployment rate | | | -0.947*** |
| NAIRU | | | -0.918*** |
| Observations | 1080 | 1080 | 1080 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

## E.2 Regression Results

Table E.6: Panel Regressions with LMI Factors

| VARIABLES | (1)<br>TFR | (2)<br>TFR | (3)<br>TFR | (4)<br>TFR | (5)<br>TFR |
|---|---|---|---|---|---|
| EPL | 0.0618** | 0.0713*** | | | |
| | (0.0260) | (0.0264) | | | |
| UnS | 0.0895*** | | 0.0522** | | |
| | (0.0228) | | (0.0214) | | |
| WB | -0.0592*** | | | -0.0462*** | |
| | (0.0103) | | | (0.00981) | |
| UB | -0.00238** | | | | -0.00321*** |
| | (0.00103) | | | | (0.00103) |
| PC maternity | 0.0448*** | 0.0470*** | 0.0442*** | 0.0433*** | 0.0504*** |
| | (0.00996) | (0.00999) | (0.0100) | (0.00992) | (0.0101) |
| PC economy | 0.0365*** | 0.0278*** | 0.0339*** | 0.0379*** | 0.0293*** |
| | (0.00993) | (0.00994) | (0.00984) | (0.00981) | (0.00984) |
| PC gender | 0.0250 | 0.0346* | 0.0320* | 0.0289 | 0.0234 |
| | (0.0191) | (0.0193) | (0.0192) | (0.0191) | (0.0194) |
| Constant | 14.78*** | 15.27*** | 15.21*** | 15.96*** | 15.50*** |
| | (0.833) | (0.828) | (0.837) | (0.811) | (0.816) |
| Observations | 1,080 | 1,080 | 1,080 | 1,080 | 1,080 |
| R-squared | 0.898 | 0.893 | 0.893 | 0.895 | 0.894 |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| Country FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| CSTT | ✓ | ✓ | ✓ | ✓ | ✓ |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table E.7: Panel Regressions with LMIs

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | TFR | TFR | TFR | TFR | TFR | TFR | TFR | TFR | TFR | TFR | TFR | TFR |
| EPL (perm. contracts) | 0.277*** | 0.185*** | | | | | | | | | | |
| | (0.0481) | (0.0472) | | | | | | | | | | |
| EPL (temp. contracts) | 0.00854 | | 0.0179 | | | | | | | | | |
| | (0.0136) | | (0.0142) | | | | | | | | | |
| Union density | 0.00985*** | | | 0.00384*** | | | | | | | | |
| | (0.00155) | | | (0.00139) | | | | | | | | |
| Union coverage | -0.00233** | | | | -0.00258** | | | | | | | |
| | (0.00108) | | | | (0.00109) | | | | | | | |
| Union concentration | 1.008*** | | | | | 0.725*** | | | | | | |
| | (0.197) | | | | | (0.158) | | | | | | |
| WB centralization | -0.449*** | | | | | | -0.264** | | | | | |
| | (0.167) | | | | | | (0.123) | | | | | |
| Gov. intervention in WB | -0.0298*** | | | | | | | -0.0327*** | | | | |
| | (0.00820) | | | | | | | (0.00767) | | | | |
| WB level | 0.00114 | | | | | | | | -0.0206** | | | |
| | (0.00869) | | | | | | | | (0.00826) | | | |
| Ext. of coll. agreements | -0.0877*** | | | | | | | | | -0.0424** | | |
| | (0.0204) | | | | | | | | | (0.0172) | | |
| Minimum wage | -0.0272*** | | | | | | | | | | -0.0212*** | |
| | (0.00561) | | | | | | | | | | (0.00582) | |
| Unemployment benefit | -0.00246** | | | | | | | | | | | -0.00321*** |
| | (0.00104) | | | | | | | | | | | (0.00103) |
| PC maternity | 0.0462*** | 0.0507*** | 0.0457*** | 0.0433*** | 0.0476*** | 0.0482*** | 0.0440*** | 0.0479*** | 0.0441*** | 0.0441*** | 0.0413*** | 0.0504*** |
| | (0.00976) | (0.0100) | (0.0100) | (0.0100) | (0.0100) | (0.00993) | (0.0100) | (0.00994) | (0.0100) | (0.0100) | (0.0100) | (0.0101) |
| PC economy | 0.0314*** | 0.0287*** | 0.0304*** | 0.0364*** | 0.0300*** | 0.0266*** | 0.0353*** | 0.0319*** | 0.0362*** | 0.0343*** | 0.0299*** | 0.0293*** |
| | (0.00981) | (0.00981) | (0.00993) | (0.00992) | (0.00986) | (0.00981) | (0.00992) | (0.00975) | (0.00994) | (0.00985) | (0.00979) | (0.00984) |
| PC gender | 0.0502*** | 0.0311 | 0.0333* | 0.0362* | 0.0406** | 0.0430** | 0.0323* | 0.0288 | 0.0312 | 0.0310 | 0.0261 | 0.0234 |
| | (0.0192) | (0.0191) | (0.0193) | (0.0193) | (0.0196) | (0.0192) | (0.0192) | (0.0191) | (0.0192) | (0.0192) | (0.0192) | (0.0194) |
| Constant | 12.26*** | 14.78*** | 15.50*** | 14.72*** | 15.87*** | 15.14*** | 15.64*** | 15.98*** | 15.86*** | 15.79*** | 16.16*** | 15.50*** |
| | (0.916) | (0.842) | (0.828) | (0.884) | (0.820) | (0.817) | (0.816) | (0.814) | (0.819) | (0.817) | (0.823) | (0.816) |
| Observations | 1,080 | 1,080 | 1,080 | 1,080 | 1,080 | 1,080 | 1,080 | 1,080 | 1,080 | 1,080 | 1,080 | 1,080 |
| R-squared | 0.908 | 0.894 | 0.893 | 0.893 | 0.893 | 0.895 | 0.893 | 0.895 | 0.893 | 0.893 | 0.894 | 0.894 |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Country FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| CSTT | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table E.8: Panel Regressions with LMI Factors and Birth Rate by Age Group

| VARIABLES | (1) Av. birth | (2) Birth 15-19 | (3) Birth 20-24 | (4) Birth 25-29 | (5) Birth 30-34 | (6) Birth 35-39 | (7) Birth 40-44 | (8) Birth 45-49 |
|---|---|---|---|---|---|---|---|---|
| EPL | 1.489 | 1.030 | 9.854*** | 1.327 | -2.820* | 0.576 | 0.191 | -0.00708 |
| | (0.907) | (0.821) | (2.110) | (2.205) | (1.633) | (1.059) | (0.404) | (0.0407) |
| UnS | 5.132*** | -1.588** | 2.534 | 10.58*** | 12.96*** | 7.858*** | 2.671*** | 0.189*** |
| | (0.710) | (0.643) | (1.652) | (1.726) | (1.278) | (0.829) | (0.316) | (0.0320) |
| WB | -2.812*** | -1.152*** | -4.750*** | -3.803*** | -4.519*** | -3.637*** | -1.257*** | -0.107*** |
| | (0.351) | (0.317) | (0.816) | (0.852) | (0.631) | (0.410) | (0.156) | (0.0158) |
| UB | -0.0891*** | -0.234*** | -0.335*** | -0.0207 | -0.00263 | -0.0217 | -0.0129 | -0.00509*** |
| | (0.0277) | (0.0250) | (0.0643) | (0.0672) | (0.0498) | (0.0323) | (0.0123) | (0.00124) |
| PC maternity | 2.425*** | -0.387 | 3.218*** | 4.851*** | 3.371*** | 4.065*** | 1.610*** | 0.151*** |
| | (0.285) | (0.258) | (0.662) | (0.692) | (0.512) | (0.332) | (0.127) | (0.0128) |
| PC economy | 1.009*** | 0.396 | 0.655 | 1.318** | 3.014*** | 1.615*** | 0.168 | -0.0142 |
| | (0.267) | (0.242) | (0.621) | (0.649) | (0.480) | (0.312) | (0.119) | (0.0120) |
| PC gender | 1.012* | -0.506 | -1.222 | 7.104*** | 2.205** | -0.757 | 0.189 | 0.0289 |
| | (0.543) | (0.491) | (1.262) | (1.319) | (0.977) | (0.634) | (0.242) | (0.0243) |
| Constant | 358.7*** | 197.3*** | 1,144*** | 867.1*** | 75.81* | 87.53*** | 124.0*** | 11.36*** |
| | (25.03) | (22.66) | (58.22) | (60.85) | (45.07) | (29.24) | (11.15) | (1.122) |
| Observations | 914 | 914 | 914 | 914 | 914 | 914 | 914 | 913 |
| R-squared | 0.908 | 0.876 | 0.944 | 0.903 | 0.881 | 0.914 | 0.924 | 0.904 |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Country FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| CSTT | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table E.9: Panel Regressions with LMIs and Birth Rate by Age Group

| VARIABLES | (1) TFR | (2) TFR | (3) TFR | (4) TFR | (5) TFR | (6) TFR | (7) TFR | (8) TFR | (9) TFR | (10) TFR | (11) TFR | (12) TFR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| EPL (temp. contracts) | 0.0423* | 0.0435* | | | | | | | | | | |
| | (0.0231) | (0.0240) | | | | | | | | | | |
| EPL (perm. contracts) | -0.140** | | -0.288*** | | | | | | | | | |
| | (0.0614) | | (0.0605) | | | | | | | | | |
| Union density | 0.00715*** | | | 0.00238 | | | | | | | | |
| | (0.00194) | | | (0.00175) | | | | | | | | |
| Union coverage | 0.00698*** | | | | 0.00473*** | | | | | | | |
| | (0.00179) | | | | (0.00180) | | | | | | | |
| Union concentration | 1.418*** | | | | | 1.146*** | | | | | | |
| | (0.261) | | | | | (0.205) | | | | | | |
| Gov. Intervention | -0.0232** | | | | | | -0.0152 | | | | | |
| | (0.0105) | | | | | | (0.0100) | | | | | |
| Level of wage bargaining | -0.0236*** | | | | | | | -0.0186** | | | | |
| | (0.00798) | | | | | | | (0.00793) | | | | |
| Ext. of coll. Agreements | -0.182*** | | | | | | | | -0.137*** | | | |
| | (0.0240) | | | | | | | | (0.0199) | | | |
| Wage bargain centralization | -0.130 | | | | | | | | | -0.179 | | |
| | (0.202) | | | | | | | | | (0.150) | | |
| Minimum wage | -0.0330*** | | | | | | | | | | -0.0290*** | |
| | (0.00712) | | | | | | | | | | (0.00758) | |
| Unemployment benefit | -0.00248* | | | | | | | | | | | -0.00639*** |
| | (0.00127) | | | | | | | | | | | (0.00123) |
| PC maternity | 0.136*** | 0.145*** | 0.142*** | 0.142*** | 0.145*** | 0.152*** | 0.145*** | 0.145*** | 0.139*** | 0.143*** | 0.136*** | 0.157*** |
| | (0.0126) | (0.0131) | (0.0130) | (0.0133) | (0.0131) | (0.0130) | (0.0132) | (0.0131) | (0.0128) | (0.0132) | (0.0132) | (0.0132) |
| PC economy | -0.0124 | -0.0276** | -0.0191 | -0.0213* | -0.0229* | -0.0346*** | -0.0245** | -0.0174 | -0.0186 | -0.0219* | -0.0264** | -0.0318*** |
| | (0.0120) | (0.0123) | (0.0121) | (0.0124) | (0.0121) | (0.0121) | (0.0122) | (0.0125) | (0.0119) | (0.0124) | (0.0121) | (0.0121) |
| PC gender | 0.0446* | 0.0576** | 0.0503** | 0.0526** | 0.0362 | 0.0800*** | 0.0484* | 0.0478* | 0.0456* | 0.0505** | 0.0429* | 0.0334 |
| | (0.0249) | (0.0252) | (0.0246) | (0.0249) | (0.0255) | (0.0250) | (0.0250) | (0.0249) | (0.0243) | (0.0249) | (0.0248) | (0.0248) |
| Constant | 11.33*** | 12.16*** | 14.31*** | 12.11*** | 12.24*** | 11.54*** | 12.86*** | 12.97*** | 13.23*** | 12.66*** | 13.37*** | 12.32*** |
| | (1.221) | (1.118) | (1.123) | (1.159) | (1.092) | (1.083) | (1.090) | (1.088) | (1.057) | (1.084) | (1.090) | (1.069) |
| Observations | 913 | 913 | 913 | 913 | 913 | 913 | 913 | 913 | 913 | 913 | 913 | 913 |
| R-squared | 0.915 | 0.894 | 0.897 | 0.894 | 0.895 | 0.898 | 0.894 | 0.894 | 0.899 | 0.894 | 0.896 | 0.897 |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Country FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| CSTT | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table E.10: Robustness: LMI Factors using Fertility at t+1

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | F.TFR | F.TFR | F.TFR | F.TFR | F.TFR |
| EPL | 0.0410* | 0.0491* | | | |
| | (0.0249) | (0.0253) | | | |
| UnS | 0.102*** | | 0.0599*** | | |
| | (0.0217) | | (0.0203) | | |
| WB | -0.0615*** | | | -0.0458*** | |
| | (0.00984) | | | (0.00933) | |
| UB | -0.00159 | | | | -0.00252** |
| | (0.000992) | | | | (0.000990) |
| PC maternity | 0.0474*** | 0.0511*** | 0.0491*** | 0.0477*** | 0.0543*** |
| | (0.00948) | (0.00953) | (0.00952) | (0.00945) | (0.00963) |
| PC economy | 0.0509*** | 0.0421*** | 0.0463*** | 0.0504*** | 0.0423*** |
| | (0.00936) | (0.00942) | (0.00930) | (0.00928) | (0.00935) |
| PC gender | 0.00824 | 0.0147 | 0.0135 | 0.00973 | 0.00640 |
| | (0.0181) | (0.0183) | (0.0183) | (0.0181) | (0.0184) |
| Constant | 14.33*** | 14.86*** | 14.61*** | 15.37*** | 14.99*** |
| | (0.747) | (0.745) | (0.752) | (0.728) | (0.734) |
| Observations | 1,060 | 1,060 | 1,060 | 1,060 | 1,060 |
| R-squared | 0.904 | 0.898 | 0.899 | 0.900 | 0.899 |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| Country FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| CSTT | ✓ | ✓ | ✓ | ✓ | ✓ |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table E.11: Robustness: Alternative Specifications

| | (1) Baseline TFR | (2) No CSTT TFR | (3) GLS TFR | (4) Wild TFR |
|---|---|---|---|---|
| EPL (perm. contracts) | 0.277*** | 0.231*** | 0.308*** | 0.285*** |
| | (0.0481) | (0.0418) | (0.0493) | (0.0600) |
| EPL (temp. contracts) | 0.00854 | -0.0135 | 0.00630 | 0.0200 |
| | (0.0136) | (0.0121) | (0.0135) | (0.0334) |
| Union density | 0.00985*** | 0.0105*** | 0.0108*** | 0.00731* |
| | (0.00155) | (0.00106) | (0.00157) | (0.00404) |
| Union coverage | -0.00233** | -0.00101 | -0.00178* | -0.00184 |
| | (0.00108) | (0.000722) | (0.00106) | (0.00349) |
| Union concentration | 1.008*** | 0.669*** | 1.068*** | 0.987 |
| | (0.197) | (0.190) | (0.200) | (0.662) |
| WB centralization | -0.449*** | -1.082*** | -0.446** | -0.581 |
| | (0.167) | (0.148) | (0.177) | (0.516) |
| Gov. intervention in WB | -0.0298*** | -0.0424*** | -0.0379*** | -0.0255 |
| | (0.00820) | (0.00905) | (0.00911) | (0.0241) |
| WB level | 0.00114 | -0.000729 | -0.00108 | 0.00572 |
| | (0.00869) | (0.00977) | (0.00960) | (0.00977) |
| Ext. of coll. agreements | -0.0877*** | 0.0507*** | -0.0984*** | -0.0736* |
| | (0.0204) | (0.0184) | (0.0212) | (0.0411) |
| Minimum wage | -0.0272*** | -0.0105* | -0.0282*** | -0.0296* |
| | (0.00561) | (0.00551) | (0.00572) | (0.0167) |
| Unemployment benefit | -0.00246** | -0.00121 | -0.00224** | -0.00245 |
| | (0.00104) | (0.000936) | (0.00104) | (0.00310) |
| PC maternity | 0.0462*** | 0.0381*** | 0.0473*** | 0.0332* |
| | (0.00976) | (0.00979) | (0.00969) | (0.0190) |
| PC economy | 0.0314*** | 0.0169 | 0.0385*** | 0.0410* |
| | (0.00981) | (0.0105) | (0.00978) | (0.0213) |
| PC gender | 0.0502*** | 0.127*** | 0.0485** | -0.0257 |
| | (0.0192) | (0.0172) | (0.0192) | (0.0628) |
| Constant | 11.45*** | 2.166*** | 2.711*** | 2.839*** |
| | (0.855) | (0.152) | (0.183) | (0.321) |
| Observations | 1,080 | 1,080 | 1,080 | 1,080 |
| R-squared | 0.908 | 0.847 | | 0.930 |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Country FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| CSTT | ✓ | No | ✓ | ✓ |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table E.12: Robustness: LMIs using Fertility at t+1

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | F.TFR | F.TFR | F.TFR | F.TFR | F.TFR | F.TFR | F.TFR | F.TFR | F.TFR | F.TFR | F.TFR | F.TFR |
| EPL (perm. contracts) | 0.205*** | 0.138*** | | | | | | | | | | |
| | (0.0482) | (0.0479) | | | | | | | | | | |
| EPL (temp. contracts) | 0.00528 | | 0.0124 | | | | | | | | | |
| | (0.0128) | | (0.0134) | | | | | | | | | |
| Union density | 0.00839*** | | | 0.00375*** | | | | | | | | |
| | (0.00148) | | | (0.00132) | | | | | | | | |
| Union coverage | -0.00166 | | | | -0.00188* | | | | | | | |
| | (0.00104) | | | | (0.00105) | | | | | | | |
| Union concentration | 1.067*** | | | | | 0.744*** | | | | | | |
| | (0.188) | | | | | (0.150) | | | | | | |
| WB centralization | -0.471*** | | | | | | -0.225* | | | | | |
| | (0.158) | | | | | | (0.116) | | | | | |
| Gov. intervention in WB | -0.0341*** | | | | | | | -0.0366*** | | | | |
| | (0.00775) | | | | | | | (0.00723) | | | | |
| WB level | 0.000768 | | | | | | | | -0.0189** | | | |
| | (0.00826) | | | | | | | | (0.00787) | | | |
| Ext. of coll. agreements | -0.0619*** | | | | | | | | | -0.0248 | | |
| | (0.0194) | | | | | | | | | (0.0163) | | |
| Minimum wage | -0.0294*** | | | | | | | | | | -0.0236*** | |
| | (0.00534) | | | | | | | | | | (0.00550) | |
| Unemployment benefit | -0.00164 | | | | | | | | | | | -0.00252** |
| | (0.00100) | | | | | | | | | | | (0.000990) |
| PC maternity | 0.0485*** | 0.0534*** | 0.0504*** | 0.0485*** | 0.0518*** | 0.0534*** | 0.0489*** | 0.0526*** | 0.0488*** | 0.0494*** | 0.0458*** | 0.0543*** |
| | (0.00931) | (0.00956) | (0.00954) | (0.00953) | (0.00956) | (0.00945) | (0.00956) | (0.00943) | (0.00954) | (0.00956) | (0.00952) | (0.00963) |
| PC economy | 0.0436*** | 0.0432*** | 0.0436*** | 0.0486*** | 0.0435*** | 0.0389*** | 0.0475*** | 0.0447*** | 0.0484*** | 0.0459*** | 0.0421*** | 0.0423*** |
| | (0.00928) | (0.00930) | (0.00942) | (0.00938) | (0.00934) | (0.00929) | (0.00941) | (0.00921) | (0.00942) | (0.00934) | (0.00926) | (0.00935) |
| PC gender | 0.0289 | 0.0118 | 0.0138 | 0.0172 | 0.0186 | 0.0243 | 0.0130 | 0.00906 | 0.0122 | 0.0121 | 0.00605 | 0.00640 |
| | (0.0182) | (0.0183) | (0.0184) | (0.0183) | (0.0186) | (0.0183) | (0.0183) | (0.0181) | (0.0183) | (0.0183) | (0.0182) | (0.0184) |
| Constant | 12.61*** | 14.50*** | 14.99*** | 14.21*** | 15.25*** | 14.59*** | 15.09*** | 15.45*** | 15.26*** | 15.19*** | 15.63*** | 14.99*** |
| | (0.826) | (0.762) | (0.745) | (0.797) | (0.739) | (0.734) | (0.734) | (0.729) | (0.736) | (0.736) | (0.738) | (0.734) |
| Observations | 1,060 | 1,060 | 1,060 | 1,060 | 1,060 | 1,060 | 1,060 | 1,060 | 1,060 | 1,060 | 1,060 | 1,060 |
| R-squared | 0.912 | 0.899 | 0.898 | 0.899 | 0.898 | 0.901 | 0.898 | 0.901 | 0.899 | 0.898 | 0.900 | 0.899 |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Country FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| CSTT | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

## E.3 Investigating the Mechanism

Table E.13: The Role of Unemployment vs. Wage Volatility for Fertility

| VARIABLES | (1) TFR | (2) TFR | (3) TFR | (4) TFR | (5) TFR | (6) TFR |
|---|---|---|---|---|---|---|
| Vol(u) | -0.118*** | | | | | -0.0973** |
| | (0.0402) | | | | | (0.0408) |
| Vol(w/p) | | 0.0747*** | | | | |
| | | (0.0239) | | | | |
| Vol(w) | | | 0.0690** | | | |
| | | | (0.0293) | | | |
| Vol(EW) | | | | -0.0994** | | |
| | | | | (0.0481) | | |
| u | | | | | -0.0280*** | -0.0217** |
| | | | | | (0.0105) | (0.0106) |
| Constant | 2.827*** | 2.698*** | 2.758*** | 2.828*** | 2.833*** | 2.864*** |
| | (0.0536) | (0.0563) | (0.0528) | (0.0598) | (0.0555) | (0.0557) |
| Observations | 120 | 100 | 100 | 91 | 120 | 120 |
| R-squared | 0.807 | 0.826 | 0.817 | 0.823 | 0.804 | 0.815 |
| Country FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table E.14: The Role of LMIs for Volatility of Employment and Wages

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Vol(u) | Vol(u) | Vol(u) | Vol(w/p) | Vol(w/p) | Vol(w/p) | Vol(EW) | Vol(EW) | Vol(EW) |
| PC maternity | -0.000507 | -0.000572 | -0.000542 | 0.561*** | 0.525*** | 0.515*** | 0.0442*** | 0.0446*** | 0.0447*** |
| | (0.000838) | (0.000834) | (0.000839) | (0.171) | (0.169) | (0.175) | (0.0147) | (0.0146) | (0.0146) |
| PC economy | -8.42e-05 | -0.00116 | -0.000888 | -0.0994 | 0.0971 | 0.0185 | -0.0243 | -0.0235 | -0.0235 |
| | (0.00100) | (0.000846) | (0.000856) | (0.198) | (0.191) | (0.195) | (0.0173) | (0.0165) | (0.0164) |
| PC gender | -0.00158 | -0.00156 | -0.00172 | 0.320 | 0.318 | 0.209 | 0.0290 | 0.0275 | 0.0282 |
| | (0.00153) | (0.00152) | (0.00154) | (0.319) | (0.317) | (0.325) | (0.0262) | (0.0263) | (0.0257) |
| EPL (perm.) | -0.00601* | | | 1.742** | | | 0.0155 | | |
| | (0.00327) | | | (0.824) | | | (0.0846) | | |
| WB centralization | | 0.0220** | | | -4.695** | | | 0.0159 | |
| | | (0.0102) | | | (2.028) | | | (0.176) | |
| UB | | | 0.000133* | | | -0.00537 | | | -0.000143 |
| | | | (7.19e-05) | | | (0.0156) | | | (0.00122) |
| Constant | 0.0193*** | -0.00171 | 0.00507* | -2.682 | 2.825*** | 1.180* | 0.119 | 0.148* | 0.157*** |
| | (0.00715) | (0.00483) | (0.00283) | (1.865) | (0.922) | (0.614) | (0.193) | (0.0778) | (0.0489) |
| Observations | 120 | 120 | 120 | 100 | 100 | 100 | 95 | 95 | 95 |
| R-squared | 0.434 | 0.442 | 0.435 | 0.525 | 0.530 | 0.496 | 0.287 | 0.287 | 0.287 |
| Country FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table E.15: 2SLS - Role of Unemployment and Wage Volatility

2nd Stage:

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | IV: EPL | IV: WB | IV: UB | IV: All | IV: EPL | IV: WB | IV: UB | IV: All |
| VARIABLES | TFR | TFR | TFR | TFR | TFR | TFR | TFR | TFR |
| Vol(u) | -0.709* | -0.591** | -0.282 | -0.521*** | | | | |
| | (0.394) | (0.292) | (0.229) | (0.199) | | | | |
| PC maternity | 0.0383 | 0.0435 | 0.0570 | 0.0466 | -0.0689 | -0.0460 | -0.239 | -0.0548 |
| | (0.0631) | (0.0540) | (0.0369) | (0.0486) | (0.101) | (0.0857) | (0.931) | (0.0793) |
| PC economy | -0.0116 | 0.000974 | 0.0340 | 0.00851 | 0.0192 | 0.0203 | 0.0112 | 0.0199 |
| | (0.0747) | (0.0617) | (0.0436) | (0.0530) | (0.0648) | (0.0584) | (0.130) | (0.0607) |
| PC gender | 0.0460 | 0.0616 | 0.102 | 0.0709 | 0.0430 | 0.0519 | -0.0235 | 0.0485 |
| | (0.122) | (0.103) | (0.0714) | (0.0911) | (0.112) | (0.100) | (0.415) | (0.103) |
| Vol(w/p) | | | | | 0.316* | 0.271** | 0.650 | 0.288** |
| | | | | | (0.162) | (0.134) | (1.819) | (0.114) |
| Constant | 3.086*** | 3.002*** | 2.783*** | 2.952*** | 2.338*** | 2.387*** | 1.972 | 2.368*** |
| | (0.338) | (0.264) | (0.197) | (0.206) | (0.256) | (0.222) | (2.016) | (0.213) |
| Observations | 120 | 120 | 120 | 120 | 100 | 100 | 100 | 100 |
| Country FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

1st Stage:

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | Vol(u) | Vol(u) | Vol(u) | Vol(u) | Vol(w/p) | Vol(w/p) | Vol(w/p) | Vol(w/p) |
| PC maternity | -0.0507 | -0.0572 | -0.0542 | -0.0663 | 0.561*** | 0.525*** | 0.515*** | 0.561*** |
| | (0.0838) | (0.0834) | (0.0839) | (0.0827) | (0.171) | (0.169) | (0.175) | (0.170) |
| PC economy | -0.00842 | -0.116 | -0.0888 | -0.0416 | -0.0994 | 0.0971 | 0.0185 | -0.0117 |
| | (0.100) | (0.0846) | (0.0856) | (0.101) | (0.198) | (0.191) | (0.195) | (0.201) |
| PC gender | -0.158 | -0.156 | -0.172 | -0.197 | 0.320 | 0.318 | 0.209 | 0.390 |
| | (0.153) | (0.152) | (0.154) | (0.152) | (0.319) | (0.317) | (0.325) | (0.319) |
| EPL (perm.) | -0.601* | | | -0.359 | 1.742** | | | 1.404 |
| | (0.327) | | | (0.339) | (0.824) | | | (0.858) |
| WB centralization | | 2.196** | | 1.714 | | -4.695** | | -3.908* |
| | | (1.016) | | (1.049) | | (2.028) | | (2.078) |
| UB | | | 0.0133* | 0.0103 | | | -0.00537 | 0.00282 |
| | | | (0.00719) | (0.00724) | | | (0.0156) | (0.0154) |
| Constant | 1.934*** | -0.171 | 0.507* | 0.596 | -2.682 | 2.825*** | 1.180* | -0.553 |
| | (0.715) | (0.483) | (0.283) | (0.949) | (1.865) | (0.922) | (0.614) | (2.282) |
| Observations | 120 | 120 | 120 | 120 | 100 | 100 | 100 | 100 |
| R-squared | 0.434 | 0.442 | 0.435 | 0.465 | 0.525 | 0.530 | 0.496 | 0.548 |
| Country FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table E.16: 2SLS - Role of Expected Wage Volatility

2nd Stage:

| VARIABLES | (1) IV: EPL TFR | (2) IV: WB TFR | (3) IV: UB TFR | (4) IV: All TFR |
|---|---|---|---|---|
| Vol(EW) | -1.851 | -0.674 | -0.867 | -0.755 |
| | (3.131) | (0.507) | (1.634) | (0.533) |
| PC maternity | 0.0382 | 0.0912 | 0.0825 | 0.0876 |
| | (0.238) | (0.0773) | (0.118) | (0.0848) |
| PC economy | -0.269 | -0.0843 | -0.115 | -0.0970 |
| | (0.534) | (0.113) | (0.275) | (0.122) |
| PC gender | -0.346 | -0.0803 | -0.124 | -0.0986 |
| | (0.795) | (0.181) | (0.408) | (0.196) |
| Constant | 4.500 | 3.386*** | 3.569** | 3.463*** |
| | (3.025) | (0.535) | (1.574) | (0.568) |
| Observations | 91 | 91 | 91 | 91 |
| Country FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |

1st Stage:

| VARIABLES | (1) Vol(EW) | (2) Vol(EW) | (3) Vol(EW) | (4) Vol(EW) |
|---|---|---|---|---|
| PC maternity | -0.0534 | -0.0433 | -0.0517 | -0.0507 |
| | (0.107) | (0.105) | (0.107) | (0.108) |
| PC economy | -0.135 | -0.195 | -0.153 | -0.183 |
| | (0.122) | (0.118) | (0.117) | (0.129) |
| PC gender | -0.242 | -0.298 | -0.227 | -0.301 |
| | (0.205) | (0.207) | (0.203) | (0.211) |
| EPL (perm.) | -0.312 | | | -0.104 |
| | (0.541) | | | (0.566) |
| WB centralization | | 1.830 | | 1.714 |
| | | (1.320) | | (1.388) |
| UB | | | 0.00514 | 0.00347 |
| | | | (0.00973) | (0.00991) |
| Constant | 1.636 | 0.300 | 0.853** | 0.509 |
| | (1.245) | (0.575) | (0.385) | (1.519) |
| Observations | 91 | 91 | 91 | 91 |
| R-squared | 0.433 | 0.447 | 0.433 | 0.449 |
| Country FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| F-stat | | | | 0.682 |
| p-value | | | | 0.567 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E.17: 2SLS - Impact of LMIs through Unemployment Volatility

2nd Stage:

| VARIABLES | (1)<br>IV: EPL<br>Av. birth | (2)<br>IV: WB<br>Av. birth | (3)<br>IV: UB<br>Av. birth | (4)<br>IV: All<br>Av. birth |
|---|---|---|---|---|
| Vol(u) | -23.87* | -17.80** | -9.669 | -16.16*** |
| | (13.95) | (8.854) | (7.285) | (6.114) |
| PC maternity | 1.234 | 1.485 | 1.821 | 1.553 |
| | (2.159) | (1.680) | (1.221) | (1.553) |
| PC economy | 1.550 | 1.634 | 1.745 | 1.656 |
| | (2.213) | (1.742) | (1.258) | (1.626) |
| PC gender | -0.280 | 0.853 | 2.368 | 1.158 |
| | (4.966) | (3.722) | (2.763) | (3.318) |
| Constant | 88.28*** | 84.16*** | 78.65*** | 83.05*** |
| | (11.60) | (8.012) | (6.248) | (6.463) |
| Observations | 109 | 109 | 109 | 109 |
| Country FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |

1st Stage:

| VARIABLES | (1)<br>Vol(u) | (2)<br>Vol(u) | (3)<br>Vol(u) | (4)<br>Vol(u) |
|---|---|---|---|---|
| PC maternity | -0.0539 | -0.0484 | -0.0566 | -0.0671 |
| | (0.0871) | (0.0860) | (0.0869) | (0.0855) |
| PC economy | 0.0759 | -0.0281 | 0.00481 | 0.0421 |
| | (0.106) | (0.0913) | (0.0922) | (0.106) |
| PC gender | -0.230 | -0.203 | -0.238 | -0.269 |
| | (0.178) | (0.175) | (0.178) | (0.176) |
| EPL (perm.) | -0.565* | | | -0.327 |
| | (0.329) | | | (0.338) |
| WB centralization | | 2.264** | | 1.827* |
| | | (1.050) | | (1.083) |
| UB | | | 0.0144* | 0.0121 |
| | | | (0.00766) | (0.00761) |
| Constant | 1.863** | -0.239 | 0.510* | 0.482 |
| | (0.745) | (0.508) | (0.294) | (0.981) |
| Observations | 109 | 109 | 109 | 109 |
| R-squared | 0.429 | 0.441 | 0.433 | 0.468 |
| Country FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table E.18: 2SLS - Impact of LMIs through Real Wage Volatility

2nd Stage:

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | IV: EPL | IV: WB | IV: UB | IV: All |
| VARIABLES | Av. birth | Av. birth | Av. birth | Av. birth |
| Vol(w/p) | 9.744* | 7.975* | 13.93 | 8.861** |
| | (5.651) | (4.418) | (24.03) | (3.897) |
| PC maternity | -3.185 | -2.106 | -5.737 | -2.646 |
| | (4.040) | (3.258) | (14.93) | (3.085) |
| PC economy | 0.472 | 0.488 | 0.433 | 0.480 |
| | (2.468) | (2.145) | (3.329) | (2.303) |
| PC gender | -1.895 | -0.996 | -4.022 | -1.446 |
| | (5.343) | (4.514) | (13.64) | (4.647) |
| Constant | 65.46*** | 67.23*** | 61.29** | 66.34*** |
| | (9.024) | (7.546) | (25.77) | (7.639) |
| Observations | 89 | 89 | 89 | 89 |
| Country FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |

1st Stage:

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | Vol(w/p) | Vol(w/p) | Vol(w/p) | Vol(w/p) |
| PC maternity | 0.687*** | 0.620*** | 0.626*** | 0.684*** |
| | (0.202) | (0.197) | (0.205) | (0.202) |
| PC economy | -0.0932 | 0.107 | -0.00580 | 0.00638 |
| | (0.238) | (0.235) | (0.240) | (0.245) |
| PC gender | 0.698 | 0.632 | 0.531 | 0.766* |
| | (0.436) | (0.425) | (0.437) | (0.434) |
| EPL (perm.) | 1.818* | | | 1.370 |
| | (0.966) | | | (1.000) |
| WB centralization | | -5.045** | | -4.200* |
| | | (2.396) | | (2.465) |
| UB | | | -0.0111 | -0.00540 |
| | | | (0.0191) | (0.0187) |
| Constant | -3.053 | 2.876** | 1.151 | -0.416 |
| | (2.253) | (1.109) | (0.730) | (2.731) |
| Observations | 89 | 89 | 89 | 89 |
| R-squared | 0.508 | 0.514 | 0.482 | 0.531 |
| Country FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure E.4: Δ TFR: Decomposition by LMI Factors

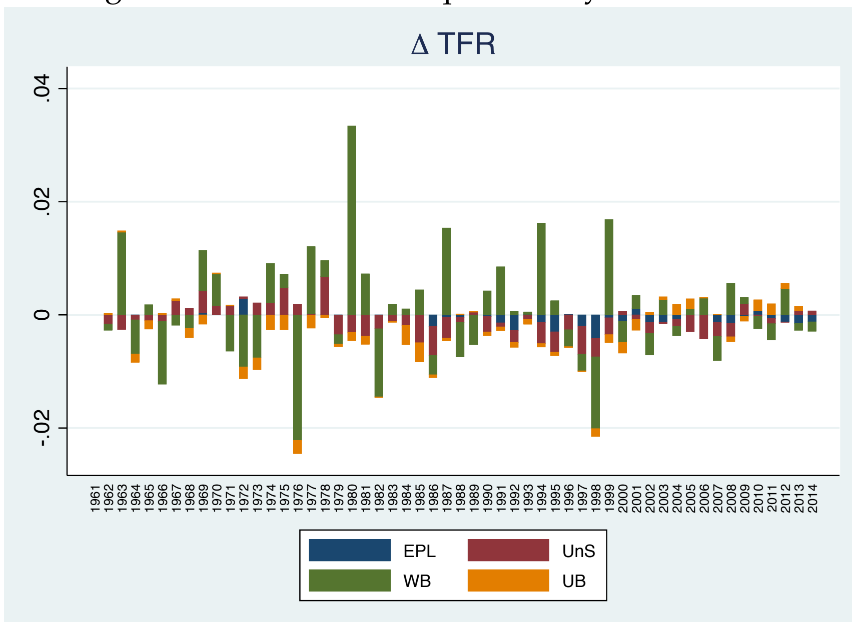
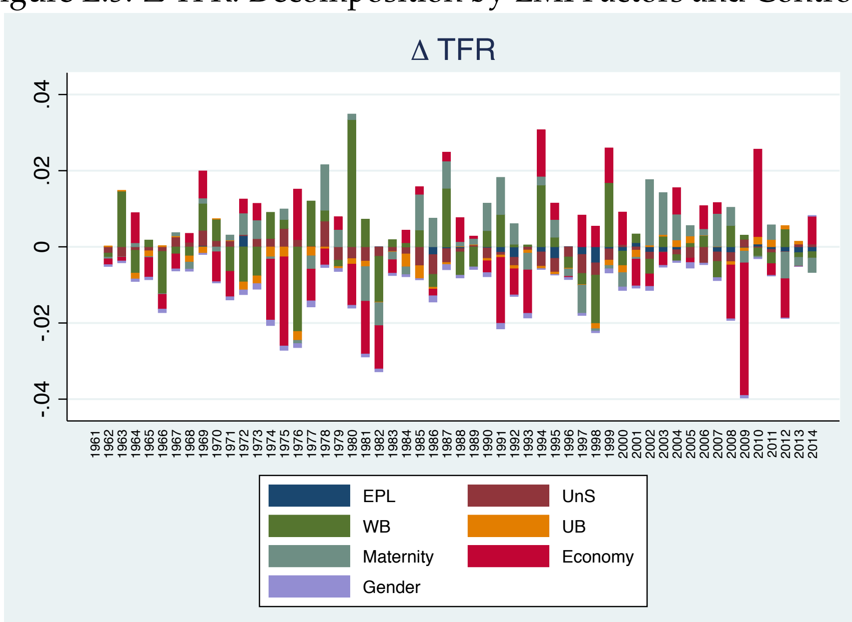



Figure E.5: Δ TFR: Decomposition by LMI Factors and Controls



## E.4 Model

Table E.19: Parameter Values

| Param. | Value | Description | Source |
|---|---|---|---|
| *Households* | | | |
| $\beta$ | 0.992 | Time discount factor | 0.97 annual rate |
| $\sigma_l^M$ | 102.4 | Disutility of labor - males | 8/24 time allocation by males to work in SS. |
| $\sigma_l^F$ | 475.5 | Disutility of labor - females | 5.3/24 time allocation by females to work in SS. |
| $\xi$ | 4.0 | Frisch elasticity of labor supply | Trigari (2009), Christoffel et al. (2009). |
| $\sigma_n$ | 0.398 | Utility weight on children | Corresponds to 2 children per household in SS. |
| $\delta_n$ | 0.025 | Children's depreciation (cost & utility) | 10 years of childhood. |
| $\psi_l$ | 0.5 | Time cost of children (curvature) | 0.33 in Doepke et al. (2007) |
| $\phi_l$ | 0.088 | Time cost of children (level) | 3/24 time allocation by females to children in SS. |
| $\phi_c$ | 0.075 | Consumption cost of children (level) | 15% of parental net income in SS (OECD). |
| *Firm production* | | | |
| $\alpha$ | 0.3 | Share of capital in production | Standard |
| $\delta$ | 0.03 | Capital depreciation rate | 12% annual rate |
| $\eta^M$ | 0.5 | Male workers exog. bargaining power | Blanchard (2010) |
| $\eta^F$ | 0.35 | Female workers exog. bargaining power | Corresponds to $ur_{SS}^F = 0.08$ |
| $\theta$ | 0.44 | Firms' preference for female workers | Corresponds to 12% wage gap in SS (16% in OECD). |
| $\rho$ | 0.65 | Elasticity of substitution males/females | Doepke et al. (2007) |
| $\kappa$ | 0.566 | Cost of posting a vacancy | Corresponds to $q_{SS}^F = 0.95$ and f=0.35 in SS (6% of GDP). |
| *Labor Market* | | | |
| $\zeta$ | 0.5 | Elasticity of matching function | Petrongolo and Pissarides (2001) |
| $b$ | 0.079 | Unemployment benefit | Corresponds to 66% replacement rate in SS. |
| $s$ | 0.041 | Separation rate | Corresponds to $ur_{SS}^M = 0.07$ and $f_{SS}^M = 0.35$ |
| $\overline{m}$ | 0.561 | CRS matching technology | Corresponds to $q_{SS}^M = 0.9$ (Ravenna and Walsh (2011)) |
| *Adjustment costs (baseline all 0)* | | | |
| $\nu$ | 0 | Wage indexation to inflation | Abbritti and Fahr (2013) |
| $\chi_w$ | 36.6 | Adjustment cost parameter - wages | Abbritti and Fahr (2013): match volatility of wage inflation |
| $\psi_w$ | 24100 | Asymmetry parameter - wages | Abbritti and Fahr (2013): match skewness of wage inflation |
| $\chi_e$ | 50 | Adjustment cost parameter - employment | Abbritti and Fahr (2013): match volatility of employment |
| $\psi_e$ | 1700 | Asymmetry parameter - employment | Abbritti and Fahr (2013): match skewness of employment |
| *Monetary policy* | | | |
| $\rho_r$ | 0.85 | Persistence of interest rate | Abbritti and Fahr (2013) |
| $\omega_\pi$ | 1.5 | Weight of inflation in Taylor rule | Abbritti and Fahr (2013) |
| $\omega_y$ | 0 | Weight of output growth in Taylor rule | Abbritti and Fahr (2013) |
| *Exogenous shocks* | | | |
| $\sigma_z$ | 0.0064 | Std. deviation of technology shocks | Smets and Wouters (2003) |
| $\sigma_{mp}$ | 0.001 | Std. deviation of monetary policy shock | Christoffel et al. (2009) |
| $\sigma_{rp}$ | 0.001 | Std. deviation of risk premium shock | Christoffel et al. (2009) |
| $\rho_z$ | 0.95 | Persistence of technology shock | Smets and Wouters (2003) |
| $\rho_{rp}$ | 0.8 | Persistence of risk premium shock | Christoffel et al. (2009) |

Figure E.6: IRF to Monetary Policy Shock

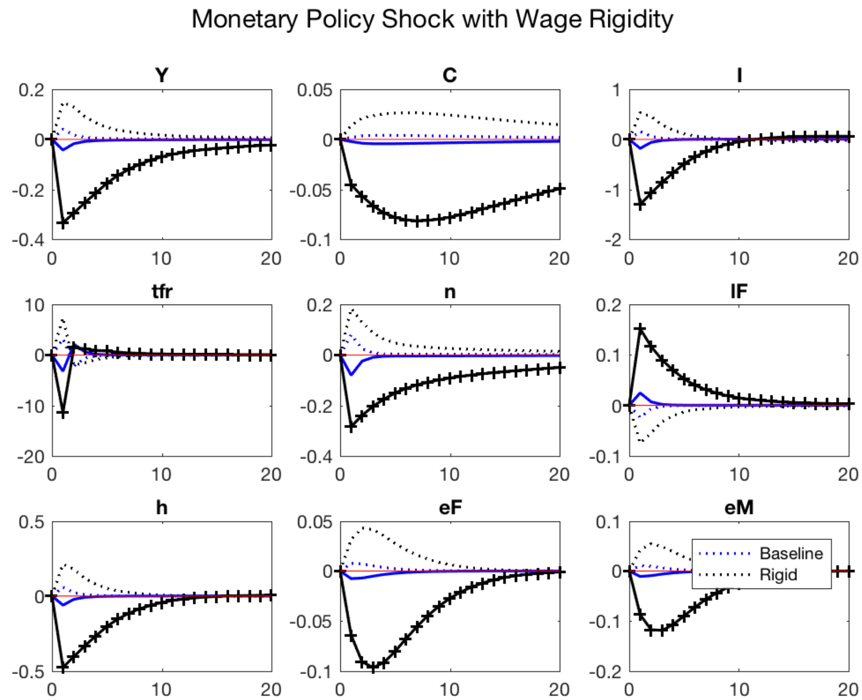
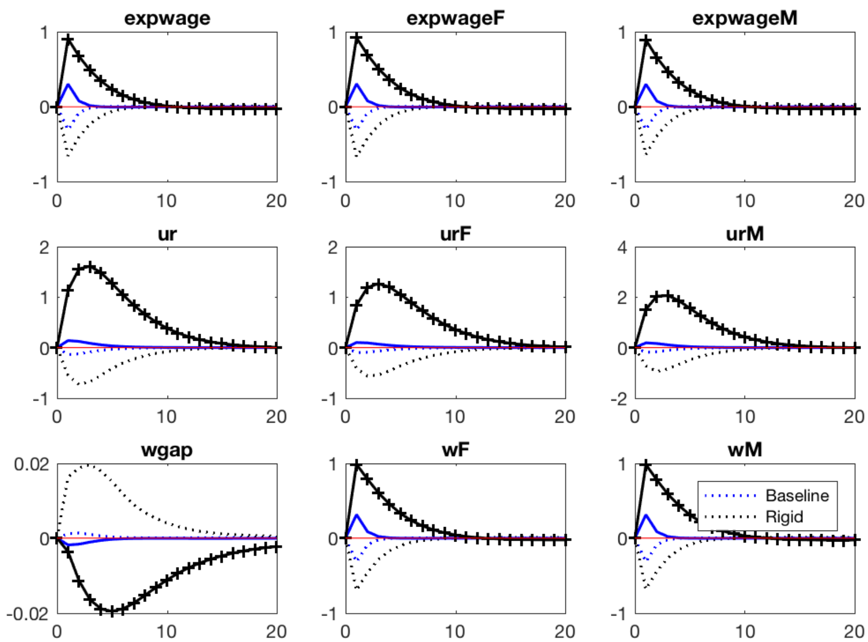


Figure E.7: IRF to Monetary Policy Shock (cont.)

Monetary Policy Shock with Wage Rigidity




Monetary Policy Shock with Wage Rigidity

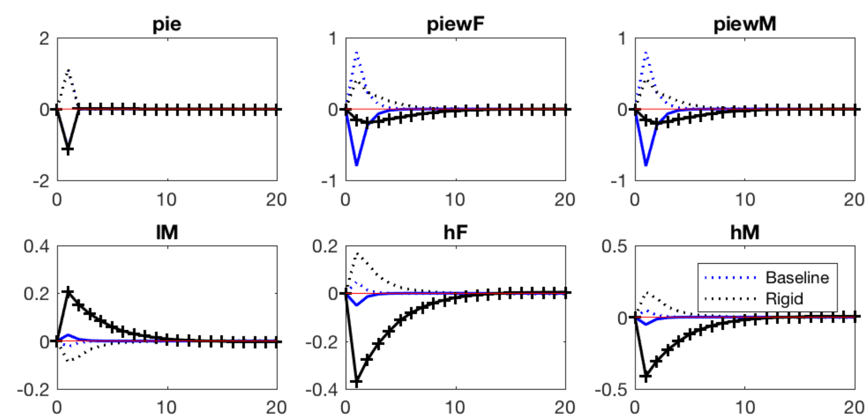


Figure E.8: IRF to Technology Shock

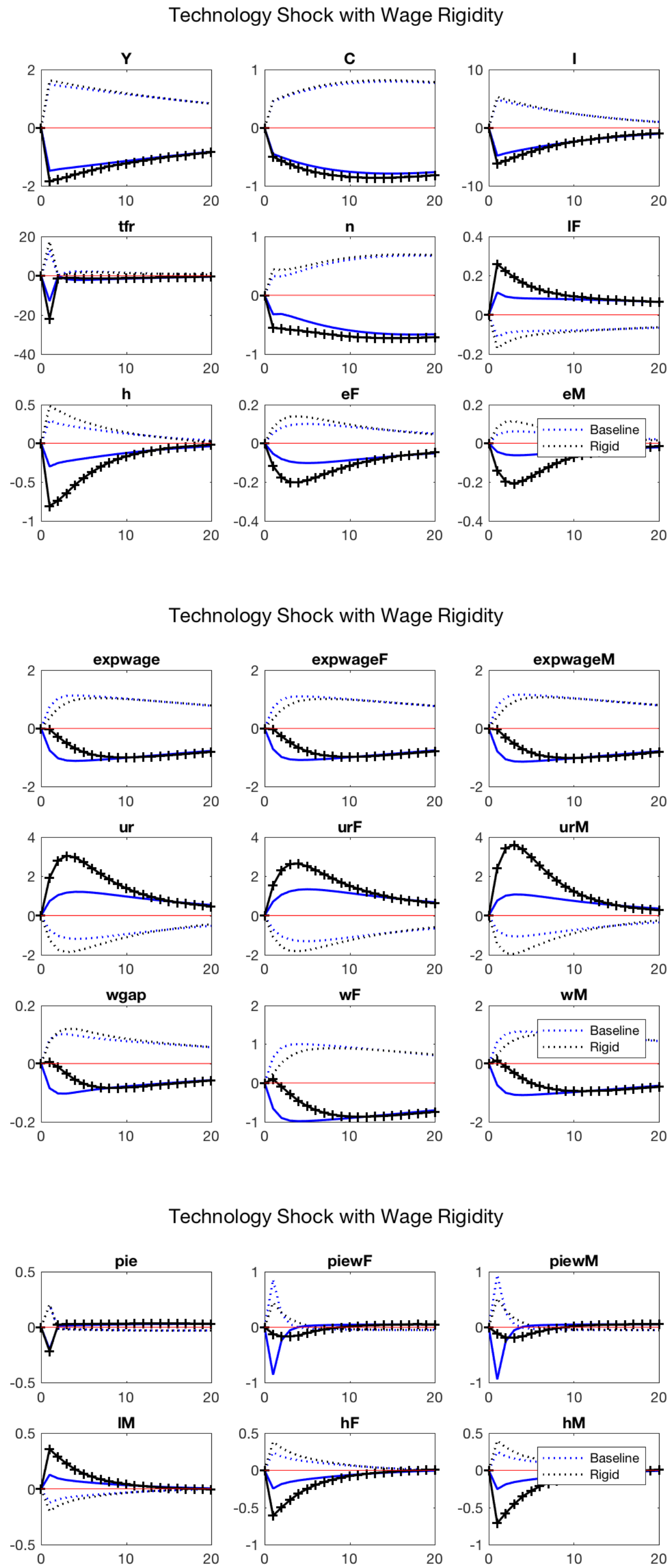


Figure E.9: IRF to Monetary Policy Shock

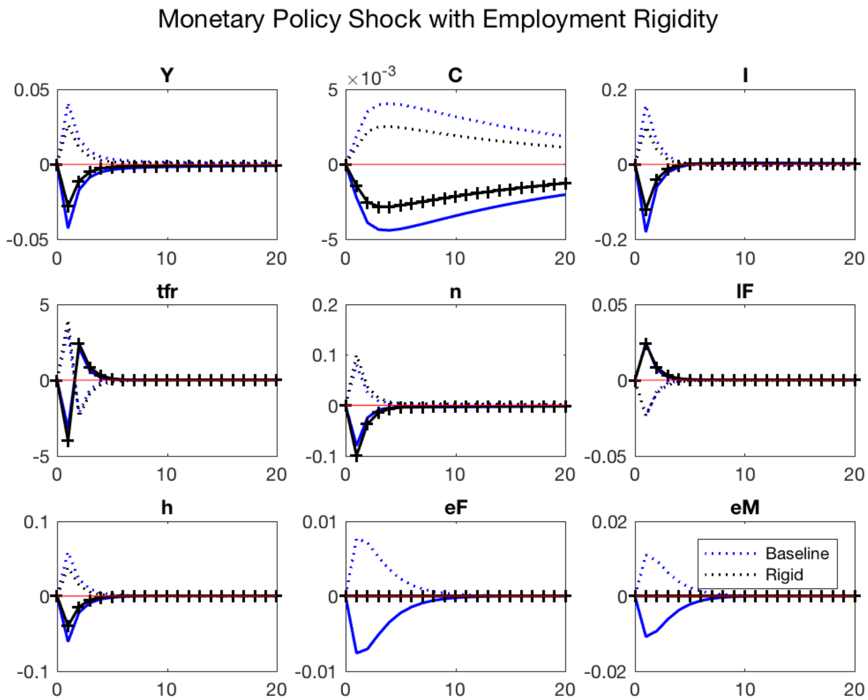
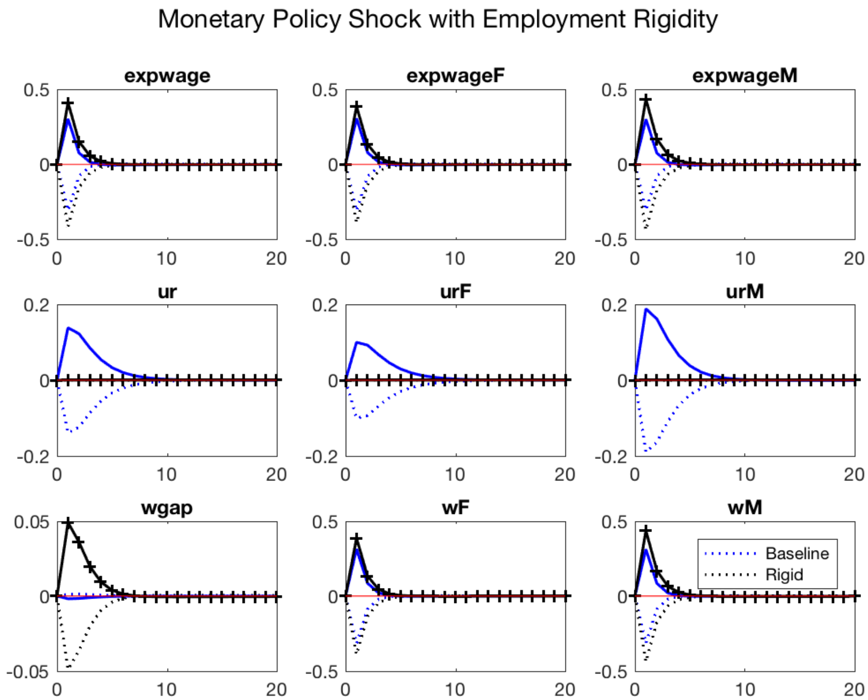


Figure E.10: IRF to Monetary Policy Shock (cont.)



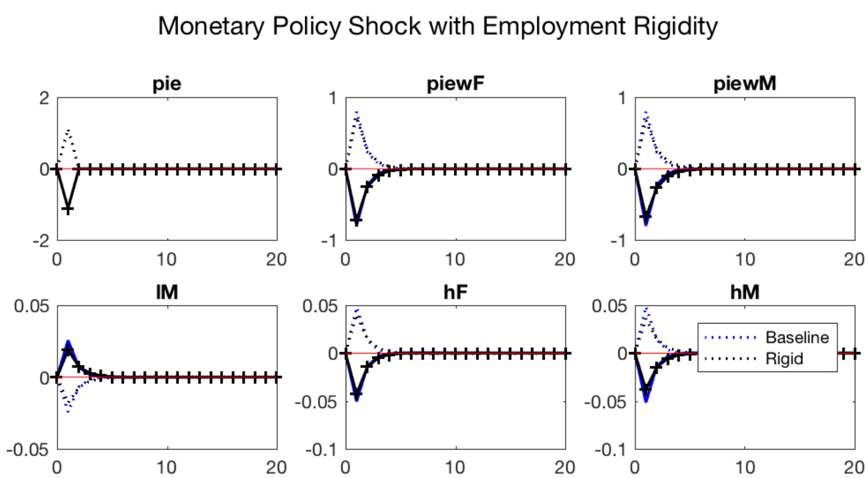
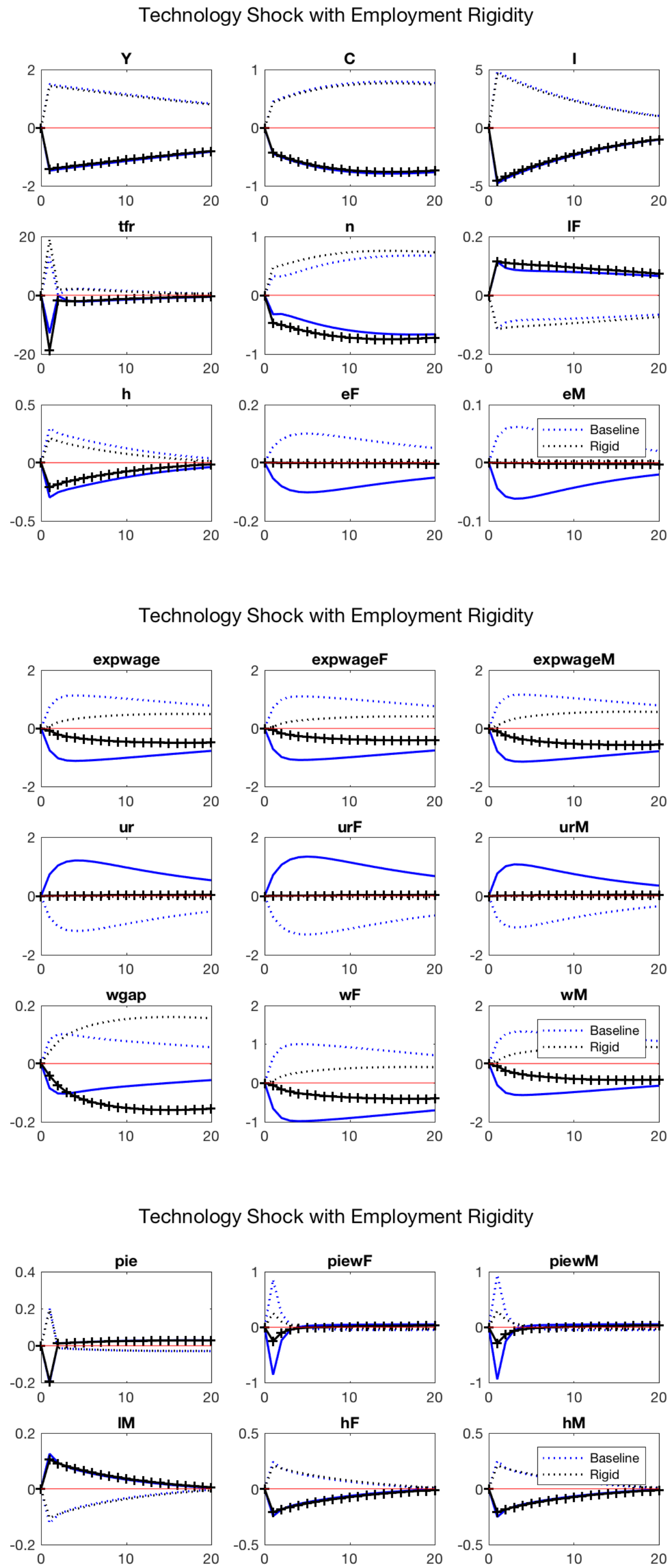



Figure E.11: IRF to Technology Shock



## E.5 Raw Data

Figure E.12: Employment Protection - Permanent Contracts

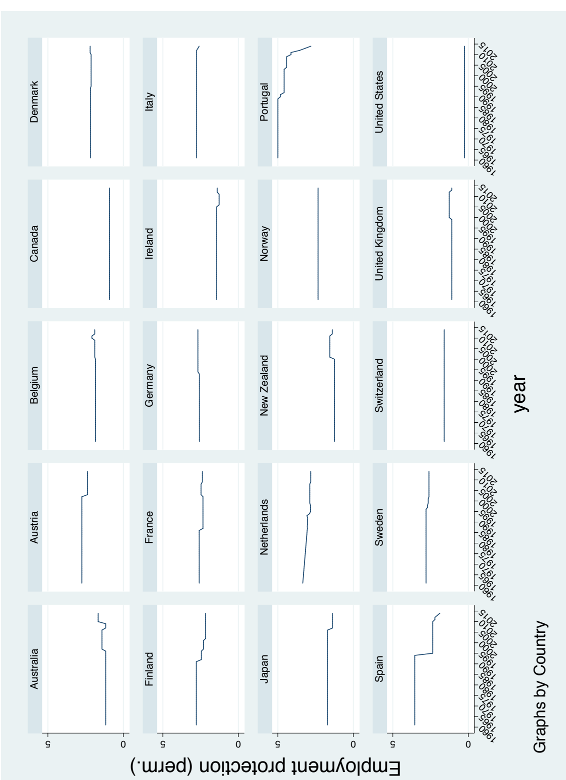



Figure E.13: Employment Protection - Temporary Contracts

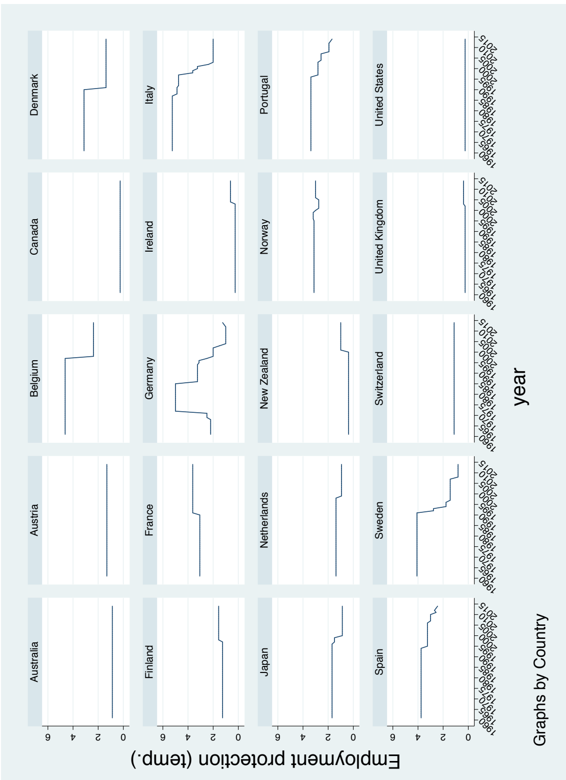



Figure E.14: Union Density

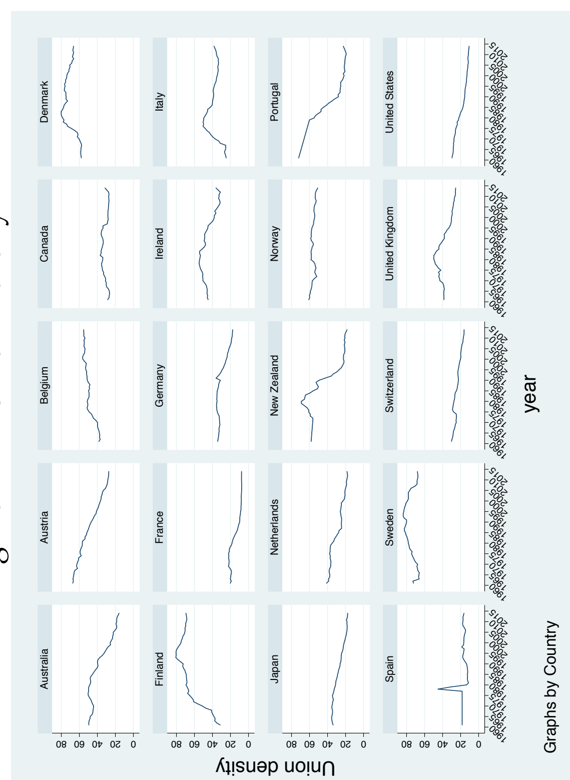



Figure E.15: Union Coverage

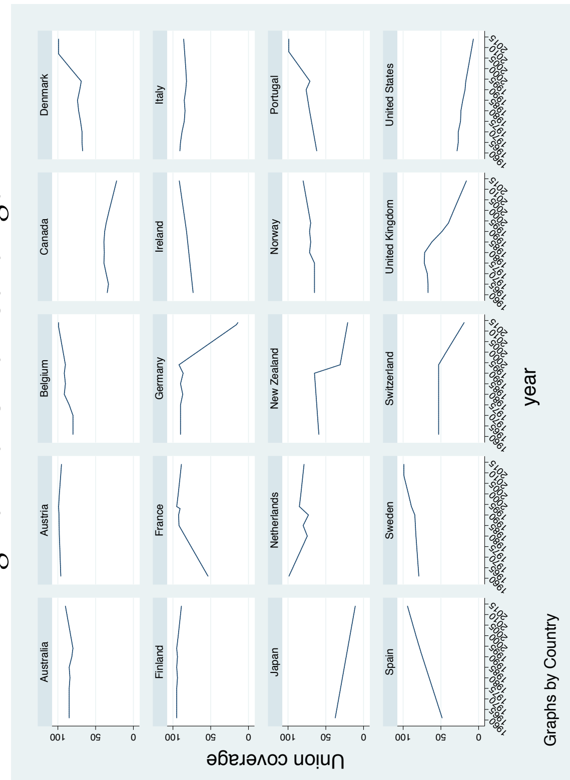


Figure E.16: Union Concentration

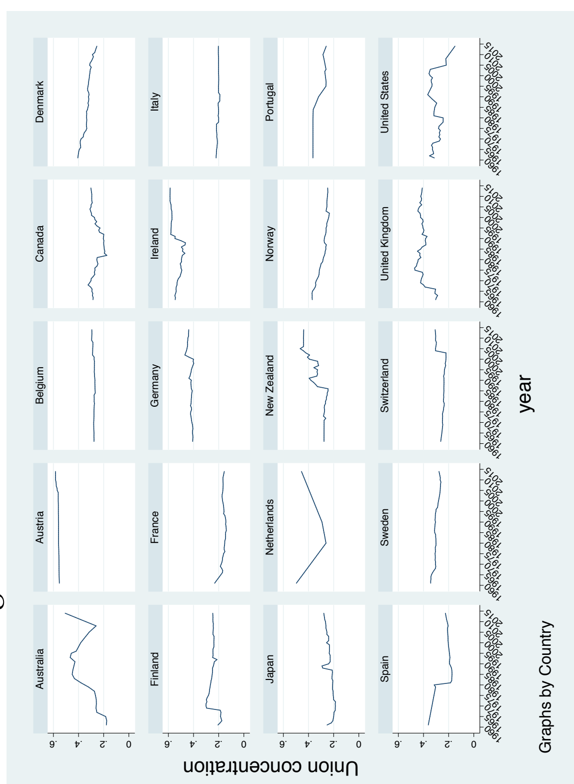



Figure E.17: Wage Bargaining Centralization

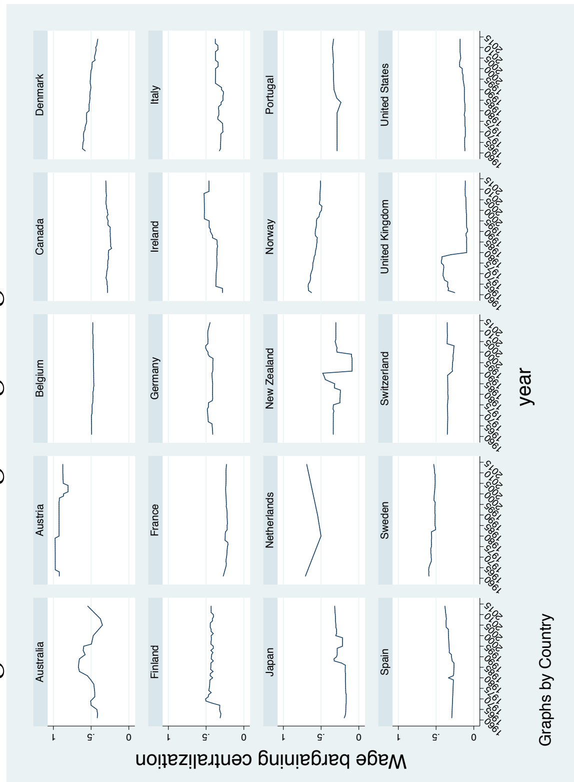



Figure E.18: Government Intervention


Figure E.19: Extension of Collective Agreements

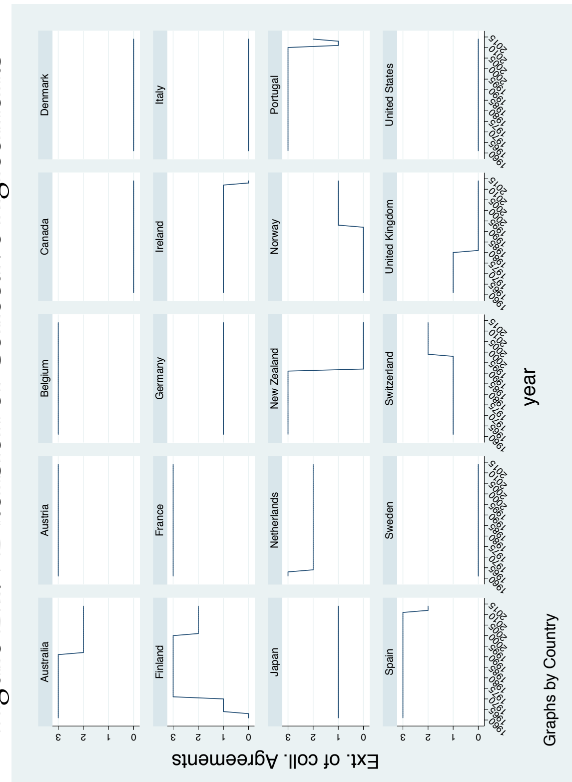


Figure E.21: Minimum Wage

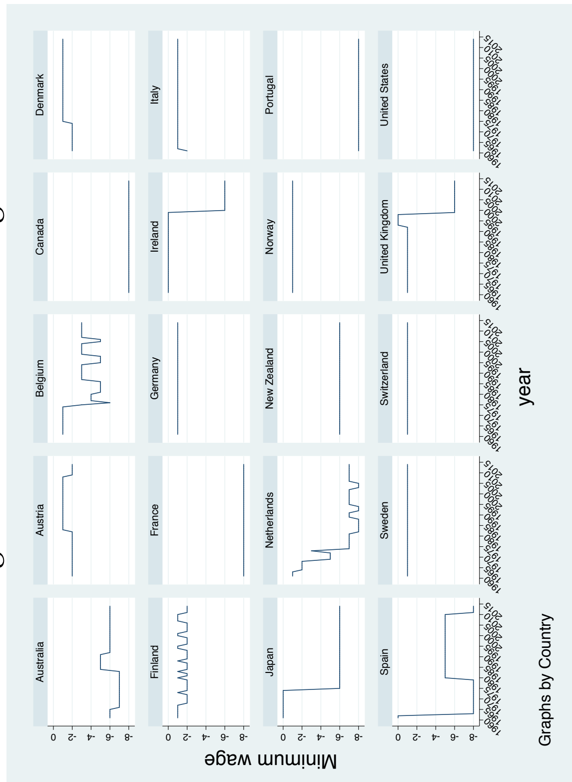



Figure E.20: Level of Wage Bargaining


Figure E.22: Unemployment Benefit

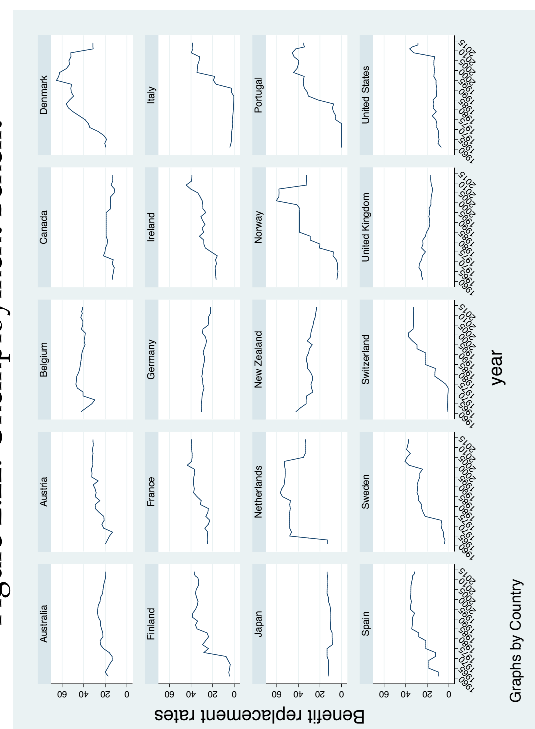


Figure E.23: Family Allowance Per Child (USD)

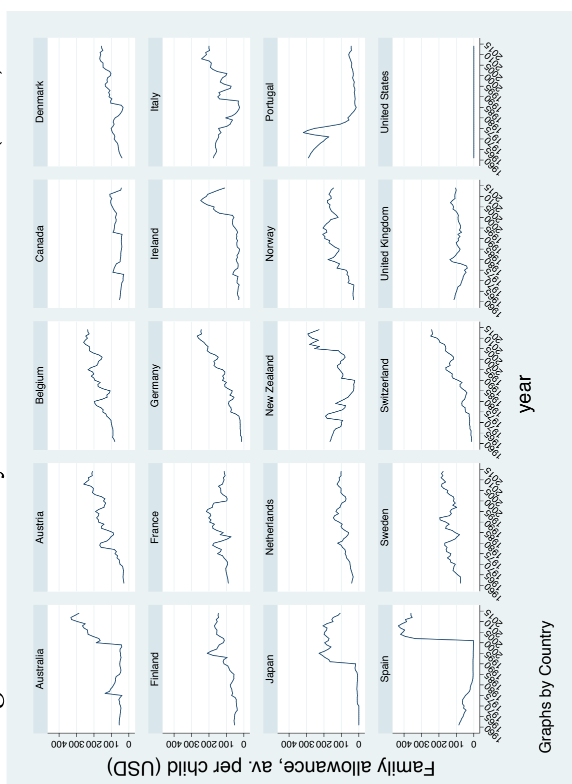



Figure E.24: Maternity Benefits

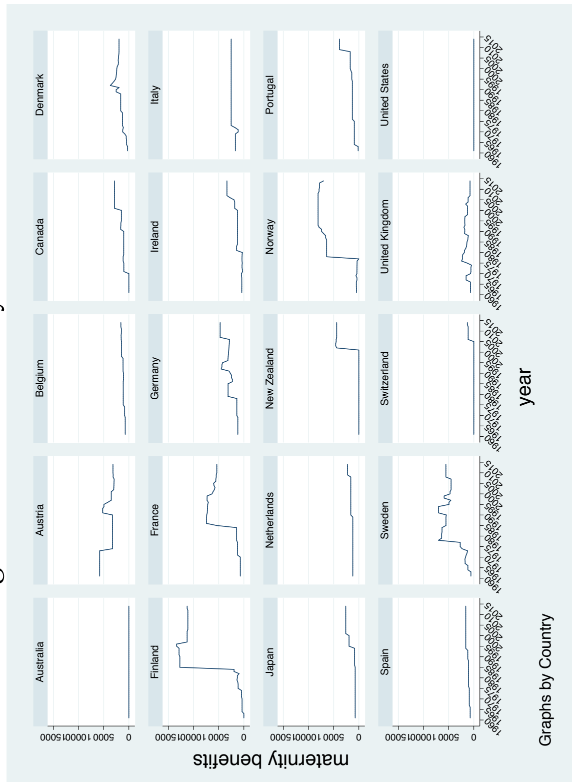



Figure E.25: Female Labor Force Participation

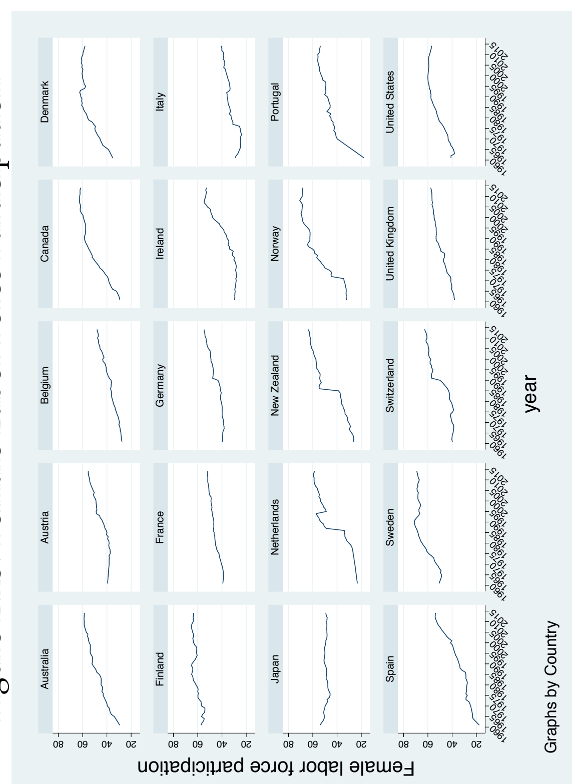



Figure E.26: Gender Wage Gap

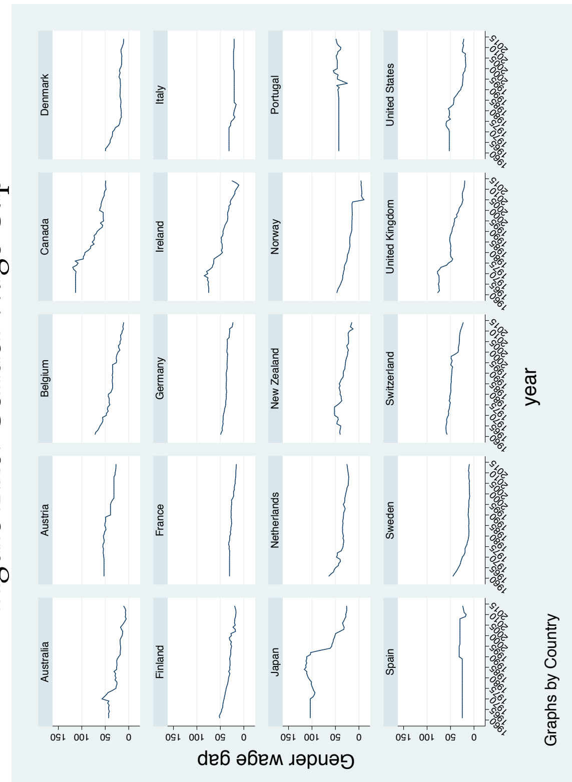


Figure E.27: GDP Growth

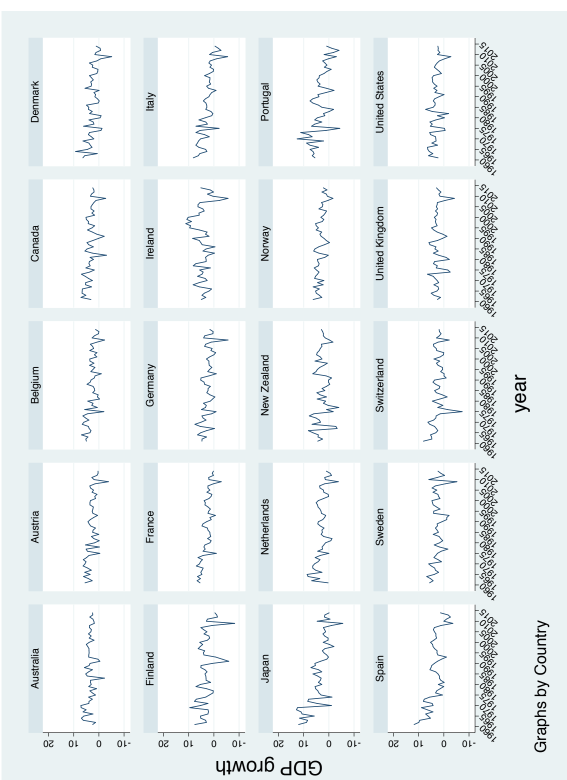



Figure E.28: Unemployment Rate

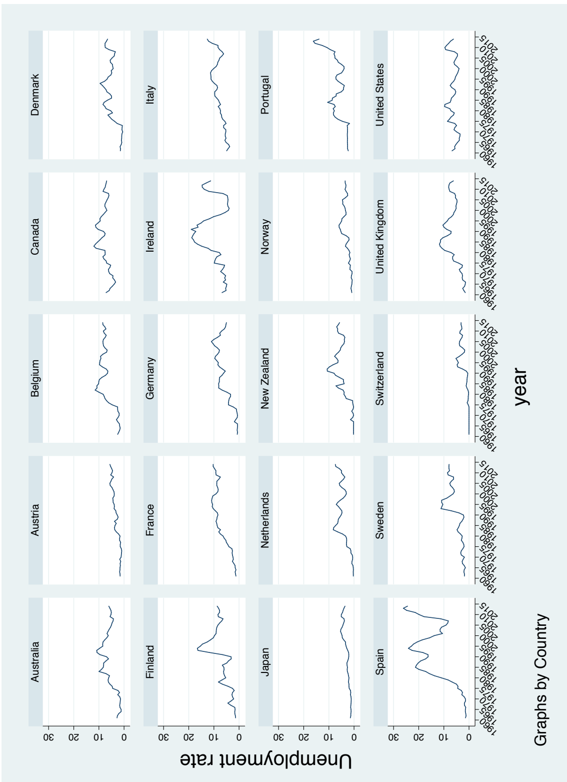



Figure E.29: NAIRU