Macroeconomic Shocks and Crime*

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Abstract

Over the last three decades, the US have witnessed a remarkable drop in crime rates, even during times of high unemployment, such as the 2007 Great Recession. We show that a sizable portion, around 25%, of the variance of US crime rates is attributable to aggregate macroeconomic shocks. We show that supply shocks, which result in both high inflation and high unemployment, boost the criminogenic effects of unemployment, but became less frequent over the years. During demand shocks, which became more frequent, the criminogenic effects of inflation and unemployment offset each other. Results are confirmed using state-level data. States where crime rates react more are those with stronger supply shocks.

JEL classification: C32, E32.

Keywords: Crime rates, macroeconomic shocks, supply, demand, monetary policy, principal components, SVAR, signs restrictions, Factor Augmented VAR.

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1 Introduction

In the United States crime rates have been dropping since the early 1990s. Several factors are believed to have contributed to this remarkable change, including increased policing and incarceration, changes in the market for crack cocaine, the legalization of abortion in the 1970s, an aging population and improved security and investigations systems (DNA analysis, surveillance cameras, etc.).[1]

Another important factor that is believed to have caused a drop in crime, especially property crimes, is economic growth. (Raphael and Winter-Ebmer(2001), aphael and Winter-Ebmer(2001)) and (Gould et al.(2002)Gould, Weinberg, and Mustard, ould et al.(2002)Gould, Weinberg, and Mustard) estimate that variation in unemployment rates explained between 12 percent and 40 percent of the decline in property crime during parts of the 1990s. A later study, (Lin(2008), in(2008)), finds slightly larger effects.[2]

But these estimates predate the Great Recession and thus come with a puzzle ChalfinMcCrary(2017): the 4 to 5 percentage points increase in US unemployment rates during the Great Recession of 2007 should have led to a 20 percent increase in property crime rates; instead, crime rates have kept on falling.

One important difference between the 1980s and the following 30 years is inflation, which went from a yearly average of 5.6 to 2.4 percent per year. Moreover, recessions, which contribute greatly to the variation in unemployment rates (GM: how much?), can have very different price dynamics. During the 1980 to 1982 recession, US consumers saw prices increase by almost 12 percent per year, while during the Great Recession, which lasted from about 2007 to 2009, the increase was just 2 percent per year.

We formalize this potential channel and complement the existing literature on crime and unemployment with a more macroeconomic approach, which allows inflation to play a role. The approach is able to capture general equilibrium effects, including small and diffused benefits that may originate from lower inflation. What may generate heterogenous crime responses to unemployment is the distinction between demand and supply shocks.

Demand shocks worsen labor market outcomes of low wage individuals, but at the same time lead to lower prices, which help individuals to make ends meet at the end of the month. Given that supply shocks combine job loss with increasing prices, they instead reinforce the detrimental effect on crime.

Figure 1(GM: can we add the UR numbers and inflation? I would probably focus on property crimes) shows that during the period characterized by low inflation, recessions and subsequent trends in unemployment have not been able to reverse the decreasing trend in crime. In this study we try to understand whether macroeconomic conditions may have contributed to this evidence.

Since the seminal paper (Blanchard and Quah(1989), lanchard and Quah(1989)) it has become quite common to use a parsimonious representation of the economy where macroeconomic fluctuations represent the outcome of the

[1]See, among others, (Levitt(2004), evitt(2004)), (Chalfin and McCrary(2017), halfin and McCrary(2017)) for a review of the literature.

[2]The literature linking wage levels to crime rates has also found fairly large elasticities, see (Gould et al.(2002)Gould, Weinberg, and Mustard, ould et al.(2002)Gould, Weinberg, and Mustard) and (Machin and Meghir(2004), achin and Meghir(2004)). A fascinating study finds that increased job opportunities in construction and manufacturing at the time of release reduce recidivism schnepel2018good.

propagation of two major types of shocks: aggregate supply and aggregate demand.[3] The former generates a negative comovement between prices and economic activity, while the latter generates a positive comovement. In modern DSGE models, typical examples of supply shocks are productivity or technology shocks, oil price shocks, labor supply shocks, while demand shocks include, among others, monetary policy shocks, government spending shocks, risk premium shocks and investment shocks.[4] While there is a huge literature on the effects of these two types of shocks on macroeconomic aggregates, little is known about their effects on crime rates.

We identify aggregate demand and aggregate supply shocks using sign restrictions [see][]Uhlig(2005) in a Structural VAR estimated on US annual macroeconomic data spanning the years 1979 to 2020 and study their effects on US crime rates. The relative importance of these factors may vary across different regions, which is why we perform the analysis not only at the national level, but also at the state one.

In line with the above evidence, our first contribution is to show that there is not a single macroeconomic factor that drives crime. Rather, it is the comovement between real economic activity and inflation which is key for its fluctuations. Shocks which imply a positive comovement between unemployment and inflation (supply shocks) significantly and persistently increase crime rates. Shocks which imply a negative comovement (demand shocks), instead, have no significant effect. Overall, macroeconomic shocks explain a sizable share of crime rates fluctuations, about 25 – 30%.

Our second contribution is to show that there is large heterogeneity in these effects across US states. Supply shocks are substantially more detrimental for crime rates in states where unemployment and inflation respond more to such shocks, and where a larger fraction of the population is urban.

The remainder of the paper is organized as follows. Section 2 discusses the econometric model and the identification strategy of aggregate supply and demand shocks. Section 3 describes the crime data and the evidence based on the SVAR model. Section 4 extends our study to state-level data. Section 5 concludes.

2 Identifying macroeconomic shocks

To study macroeconomic and crime dynamics, we use a Vector Autoregressive (VAR) model. Let y_t be a n-dimensional time series vector including the following set of US variables: GDP growth, the unemployment rate, GDP deflator inflation, the federal funds rate and crime rates.[5] We assume that y_t has the following VAR representation

$$A(L)y_t = B_0 u_t \tag{1}$$

[3]See, for instance, (Angeletos et al.(2020)Angeletos, Collard, and Dellas, ngeletos et al.(2020)Angeletos, Collard, and Dellas) and (Avarucci et al.(2022)Avarucci, Cavicchioli, Forni, and Zaffaroni, varucci et al.(2022)Avarucci, Cavicchioli, Forni, and Zaffaroni).

[4]See, among others, (Smets and Wouters(2007), mets and Wouters(2007)) and (Christiano et al.(2014)Christiano, Motto, and Rostagno, hristiano et al.(2014)Christiano, Motto, and Rostagno).

[5]We consider only crimes for economic motives which is defined as the sum of property crimes (burglary, larceny and motor vehicle theft) plus robbery.

where $A(L) = I - A_1L - ... - A_pL^p$ is a matrix of polynomials in the lag operator, B_0 is a $n \times n$ matrix of coefficients containing the contemporaneous impact of the shocks u_t on the vector y_t and $u_t \sim WN(0, I)$ is an orthonormal vector of structural shocks. Let $\varepsilon_t = B_0u_t$ be the reduced-form residuals and let $\Sigma = E(\varepsilon_t\varepsilon_t')$ be the variance-covariance matrix of ε_t.

The structural Vector Moving Average (VMA) representation is given by

$$y_t = B(L)u_t \tag{2}$$

where $B(L) = A(L)^{-1}B_0$.

We first identify two broad categories of macroeconomic shocks: aggregate demand and aggregate supply shocks. The two differ for their implications in terms of comovement between real activity and prices: negative for the former and positive for the latter. These implications are used to identify the two shocks. More specifically, we use sign restrictions (see Uhlig, 2006) and impose that a negative supply shock simultaneously reduces output and increases prices and the unemployment rate, while a negative demand shock is assumed to reduce output and increase inflation and the unemployment rate.

In an extended version of the model, we further distinguish between monetary policy shocks and non-policy demand shock. To do so, we use the implication that while non-policy demand shocks generate a positive comovement between prices, output and the interest rate, a monetary policy shock generates a negative comovement between the interest rate and both prices and economic activity. In this extended version of the model supply shocks are identified as before. A negative non-policy demand shock is assumed to simultaneously reduce output and the interest rate and increase inflation and unemployment. A contractionary monetary policy shock, instead, simultaneously reduces output and prices and increases the unemployment rate and the interest rate.

In both models, the sign restrictions are imposed on the contemporaneous effects only, i.e. first three columns of B_0. These restrictions are pretty standard in the SVAR literature and have been previously employed in (Debortoli et al.(2023)Debortoli, Forni, Gambetti, and Sala, ebortoli et al.(2023)Debortoli, Forni, Gambetti, and Sala), among others.

Together with the identification of the three macroeconomic shocks, we also identify a "crime shock" as the part of the crime variable (the last variable in y_t) which is orthogonal to current and past values of macroeconomic variables, i.e. the fifth shock of the Cholesky representation of y_t. From our perspective, this shock is not interesting per sè, but it helps in two respects. First, it allows for the presence of a shock which drives crime and is disconnected from economic outcomes. Indeed, it is very plausible to believe that a potentially important part of fluctuations in crime are actually attributable to factors which are disconnected from macroeconomic outcomes. For instance incarceration policies, institutional factors, etc. Second, the three macroeconomic shocks can be found by rotating the first four shocks of the Cholesky representation instead of rotating all the five shocks. This reduces the number of free parameter of the rotation matrix and therefore increases the precision of the identification procedure.

The implementation of the identification proceeds as follows. Let S be the Cholesky factor of Σ, i.e the unique lower-triangular matrix with $S'S = \Sigma$. Let the matrix of contemporaneous effects be

$$B_0 = S\begin{pmatrix} H & 0 \\ 0' & 1 \end{pmatrix}$$

where H is a $n-1 \times n-1$ orthogonal matrix, i.e. $HH' = I$ and 0 is a $n-1 \times 1$ vector of zeros. A draw for H is obtained using Givens rotations and assuming that the underlying matrix parameters are uniformly distributed in $[0, 2\pi]$. A candidate draw is retained if the first three columns satisfy the sign restrictions discussed above for the three structural shocks. Let $\tilde{H}$ be the first three columns of the retained draw. The structural impulse response functions of the three shocks are given by $\tilde{B}(L) = A(L)^{-1}S\tilde{H}$.

The VAR is estimated using a Bayesian approach with a flat prior for the parameters and one lag of the dependent variable, as suggested by the BIC criterion.[6]

3 The effects on crime rates

In this section we discuss the data on crime rates and present the main results obtained using aggregate US data.

3.1 Data

We use data from the Summary Reporting System (SRS) dataset of the *Crime Data Explorer* of the Federal Bureau of Investigation (FBI). The data are available at the national and state levels at the yearly frequency from 1979 to 2020, and consist of reported crimes from law enforcement agencies submitted to the Uniform Crime Recording (UCR) Program of the FBI.[7] We focus on crimes for economic motives, defined as total property crime (the sum of burglary, larceny and motor vehicle theft) plus robbery, per 10000 people.

Figure 1 displays the evolution of US crime rates from 1979 to 2020. Grey shaded areas refer to NBER recession dates. We observe a marked decline in US crime rates since the early 1990s, of about 60%. To put this into perspective, 500 crimes per 10000 inhabitants were on average reported to the FBI every year in the early 1980s, while this number dropped to around 200 by 2020. One interesting observation is that crime rates did not rise following the Great Recession, sparking a debate on the potential disconnect between real economic activity and crime. This puzzling phenomenon has been largely discussed in the crime literature. However, no general consensus has been reached on its source. In the next sections, we propose a macroeconomic interpretation to this puzzle.

[6]The details of the Bayesian estimation are described in the Appendix.

[7]The only exception is Mississipi, for which crime data are available from 1995 onwards. We include a detailed description of the data in the Appendix.

3.2 Evidence

Figure 2 reports the estimated impulse responses of macroeconomic variables and crime rates to supply and demand shocks, column (a) and (b) respectively, estimated in the two-shock identification. Solid lines are point-wise median responses, while shaded areas are 68% probability density intervals based on 1000 draws from the posterior distribution of the impulse responses. The x-axis refers to time, in years, after the innovations occurred.

We normalize the two shocks to have a positive impact response on inflation, so we consider the effects of a negative supply shock and a positive demand shock. A negative supply shock generates a persistent and significant increase in the unemployment rate, inflation and the federal funds rate, and a reduction in GDP growth. A positive demand shock increases GDP growth, inflation and the federal funds rate, while it decreases the unemployment rate. The responses of unemployment and inflation appear less persistent than for the aggregate supply shocks.

As far as crime is concerned, the supply shock permanently and significantly increases crime rates. A shock that increases the unemployment rate by 0.2% and inflation by 0.4% on impact generates approximately 50000 new crimes per year, every year, after the shock. The aggregate demand shock has instead no significant effects. This result supports the idea that there is not a single macroeconomic factor, real economic activity or inflation, which matters for crime dynamics. If this were the case, the response of crime rates would have the sign implied by the relevant variable: negative if unemployment, positive if inflation were the relevant factor. Our results show that both variables matter. The large response of crime rates to the supply shock is the outcome of higher inflation and lower economic activity.

We conclude that, rather than a single macroeconomic factor, it is the comovement between real economic activity and inflation which is key for the dynamics of crime rates: crime rates significantly increase when the economic slowdown is coupled by an increase of inflation, but are unaffected when demand forces are at work, as the effects of the economic slowdowns on crime tend to be offset by a reduction in prices.

Table 1 shows the quantitative relevance of the two shocks for crime rates, on average over the sample considered. The supply shock explains around 15% of the variance of crime rates at all the horizons, while the demand shock only 8%. Overall, about 20-25% of the variance of crime rates is attributable to the two macroeconomic shocks, while the remaining share is explained by shocks other than the macroeconomic ones considered.

To get further insights on the role of the comovement of unemployment and prices, we distinguish between a non-policy demand shock and a monetary policy shock. Figure 2 reports the results for this second three-shock identification [GM: I would put this in a separate figure. And what is the advantage of showing 2 vs. 3 factor shocks? should we put one in the appendix? adding monetary shock seems to lower CIs]]: column (c) reports the impulse response functions of the supply shock, column (d) the non-policy demand shock and column (e) the monetary policy shocks. The effects of supply shocks are almost identical to those estimated with the two-shock identification strategy. Non-policy demand shocks have non significant effects, whereas the monetary policy shock significantly increases crime rates for the first few years after the shock has occurred. The difference can be explained by looking at the size of the response of unemployment and inflation for the two different shocks. For the non-policy shock, the peak effects are of similar magnitude: 0.6% for unemployment and 0.3% for inflation. The main difference, however, is that now the effects on inflation are substantially more persistent than those estimated for the non-policy shock. The overall effect on prices is much larger for the monetary policy shock than for the non-policy shock, while the effect on unemployment is similar. This result confirms our previous interpretation that it is the joint behavior of inflation and unemployment which determines the effect on crime rates.

From Table 1, even in the three-shock identification supply remains, among the three, the main driver of crime rates, explaining again around 17% of the variance of the series. Demand shocks explain around 8% each. The results suggest that around 30% of the variance of crime fluctuations is now attributable to the three macroeconomic shocks. Overall, the results depict a clear and important link between economic fluctuations and crime rates, although the bulk of fluctuations in crime rates (around 70%) appear to be independent of the macroeconomy.

We repeat the analysis using crime rates defined using homicides plus aggravated assault only, namely considering crimes for non-economic motives only. Figure 5 reports the impulse response functions in the two models. Using violent crime rates instead, the effects of macroeconomic shocks are substantially smaller and not significant, suggesting that only crimes related to economic motives are sensitive to macroeconomic fluctuations.

As a robustness check, we repeat the empirical analysis replacing aggregate crime rates with the first principal component of the panel of the 50 US states crime rates. This is particularly important in the next section where we will discuss a model for state-level data based on this specification. Panel (b) of Figure 5 in the Online Appendix reports the results. The results are almost identical to those obtained with aggregate crime rates confirming a primary role played by the supply shock and a much modest role for demand shocks, especially non-policy shocks. From Table 1, we can observe that also in terms of variance decomposition the results are extremely similar: around 20-30% of the variance of crime rates is accounted for by the two or three macroeconomic shocks considered.

The main conclusion of this subsection is that only supply shocks have significant and persistent effects on crime rates. Our interpretation is that this finding depends on the fact that the two channels, economic activity and inflation, reinforce each other. On the other hand, demand shocks tend to have non-significant effects since the two channels tend to offset each other.

4 State-level analysis

We extend our analysis and consider state-level data. Understanding potential heterogeneity in the transmission of macroeconomic shocks can shed further light on the channels through which macroeconomic shocks affect crime.

Figure 6 in the Online Appendix reports the state level-data for property crimes plus robbery.

4.1 A model for state-level crime rates

[GM: should we move this earlier, where the national model is explained?] The empirical model used to carry out the state-level analysis is a Factor-Augmented VAR model (FAVAR, see (Bernanke et al.(2005)Bernanke, Boivin, and Eliasz, ernanke et al.(2005)Bernanke, Boivin, and Eliasz)) with four observable factors (the four macroeconomic variables used before in the aggregate analysis) and one unobserved factor, the first principal component of the panel of the 50 US states crime rates.

More formally, let x_t be the vector including the crime rates for the 50 US states. We assume that crime rates are the sum of two orthogonal components, a component which is common across states driven by macroeconomic shocks, χ_t, and an idiosyncratic component, ξ_t containing state-specific shocks:

$$x_t = \chi_t + \xi_t \tag{3}$$

Let y_t be the vector including the four macroeconomic variables considered before, namely GDP growth, inflation, unemployment and the interest rate, and the first principal component of state-level crime rates. As usual in the FAVAR model, the common component is assumed to be a static combination of the vector y_t. In particular, we assume that

$$\chi_t = \Lambda y_t. \tag{4}$$

where Λ is a 50×5 matrix of coefficients. By replacing equation (2) into equation (4), we obtain the structural representation of the common component of the state-level crime rates in terms of structural macroeconomic shocks

$$\chi_t = \Lambda B(L) u_t \tag{5}$$

where $\Lambda B(L)$ are the structural impulse response functions of the state-level crime rates. The response of the state-level crime rates to the three identified shocks are given by $\Lambda \tilde{B}(L)$ where $\tilde{B}(L)$ is the matrix of the macroeconomic variables and the crime factor to the three shocks supply, non-policy demand and monetary policy.

The coefficients of the matrix Λ are estimated from the OLS regression of the state-level crime rates, x_t, on the vector of macroeconomic variables y_t. The columns of the polynomial matrix $B(L)$ corresponding to the three macroeconomic shocks, namely supply, demand and monetary policy shocks, are obtained using the identification discussed in the previous section.

4.2 Evidence

We obtain the state-level responses to the three shocks estimated using the model discussed above. The first row of Figure 3 reports the point-wise median of the impulse response functions of state level crime rates to the three shocks. The responses with at least one positive significant effect over the horizon considered are displayed in solid red, while the remaining ones in dashed blue. Again, the x-axis refers to time, in years, after the innovations occurred.

As far as supply shocks are concerned, most states display at least one positive significant effect. Only 9 states, out of the 50 considered in the analysis, show effects that are never significant over the horizon considered. There is, however, a high degree of heterogeneity in the responses. In terms of magnitude, the impact response ranges from close to zero up to 20 crimes per capita. As for the model with aggregate data, the effects appear to be permanent. For demand shocks, crime rates do not display any significant effect for the majority of US states, consistently with the responses from the model on aggregate data. For non-policy demand shocks, there are only 11 states with at least one significant effect over the horizon considered, and 17 for the monetary policy shock. Moreover the magnitude of the responses are much smaller than for the supply shock, with the exception of a few cases.

From the estimated impulse response functions, we derive two measures which summarize the sensitivity of state-level crime rates to macroeconomic shocks. These measures are the average of the impulse response functions to supply shocks over an horizon of three years and twelve years, respectively. In what follows, we focus on supply shocks only as these are the only shocks generating significant and sizable responses for the majority of US states.

Figure **??** reports the sensitivity measures for all the states with significant responses for at least one period (non-significant responses are in in white). Table 2 reports the list of states belonging to the most sensitive (at least one significant response within the first three years and more than 10 crime per year on average during the first three years) in the second column and the least sensitive (no significant effects) on the fourth column. It also reports the state sensitivity for each state in the list. The least sensitive states are mostly located in the southeast region, with a few exception (Nebraska, Utah and New Mexico). The most sensitive states are those located in the northeast region and other states with high metropolitan areas like California. Nevada, California and New York represent the top three in terms of sensitivity, with 18.3, 17.5 and 17.3 crime rates per year respectively.

We exploit the state-level responses heterogeneity to assess potential causes of crime sensitivity, to better understand, in particular, the importance of inflation and real economic activity as channels for the propagation of macroeconomic shocks. To do so, first of all we estimate model (5) using state-level unemployment and inflation and compute the responses to the three shocks. Second and third rows of Figure 3 report the responses of unemployment rate and inflation respectively. Again in solid red we display the responses in which there is at least one positive significant effects, in dashed blue the remaining ones. Responses are quite similar across states in terms of shapes but with important differences in terms of magnitude. Unlike crime rates the response of both unemployment and inflation are significant for at least one horizon for almost all the states.

From the responses we construct a measure of sensitivity as the average responses of unemployment and inflation over the first three years. With these measures at hand, we compute the partial correlations with the sensitivity of crime rates using a bunch of controls: urban population, population density, percent of people below the poverty rate, state GDP[8] and the share of (state) government spending over (state) GDP.

Table 2 reports the partial correlation coefficients and the associated p-values. Of course inference has to be taken with grain of salt since the variables are estimates rather than observable variables. For supply shocks, crime sensitivity displays a high correlation with both unemployment sensitivity and inflation sensitivity, 0.55 and 0.42 respectively. Crime rates tend responds more to supply shocks in states where unemployment and inflation react more. The result confirms our interpretation that both variables are important in the transmission on macroeconomic shocks on crime rates. Another important factor turns out to be urban population, with a conditional correlation of 0.55. For completeness we also run the same analysis for demand shocks, see Table 3 in the Online Appendix. Not surprisingly,

[8]This last variable is important to make sure that sensitivity is not higher simply because the state contributes more to aggregate variables.

since the IRF are not significant for most of the states and thus not informative, correlations tend to be very low.

The state-level analysis confirms and reinforces the main conclusions drawn from the analysis on aggregate crime rates. Supply shocks represent the major factor behind the linkages between economic fluctuations and crime rates. Unfavorable supply shocks significantly increase crime rates. The reason is that both unemployment and inflation are important factors and the detrimental effect of the two in combination increase crime rates.

5 Concluding remarks

We provide novel evidence on the link between macroeconomic fluctuations and crime.

We show that aggregate supply shocks exert the largest effect on crime rates, while both policy and non-policy aggregate demand shocks play a limited role. This finding suggests that what matters for crime dynamics is the comovement between real economic activity and inflation. A simultaneous increase in unemployment and inflation (supply shocks) is particularly detrimental for crime. On the contrary, when the two variables move in opposite direction (demand shocks) their effects tend to offset each other. Results are confirmed using state-level data, although the responses to aggregate supply shocks present a large extent of heterogeneity. States where crime rates react more are those where both unemployment and inflation respond more and where urban population is higher.

References

George-Marios Angeletos, Fabrice Collard, and Harris Dellas. Business-cycle anatomy. *American Economic Review*, 110(10):3030–3070, 2020.

Marco Avarucci, Maddalena Cavicchioli, Mario Forni, and Paolo Zaffaroni. The main business cycle shock (s): Frequency-band estimation of the number of dynamic factors. 2022.

Ben Bernanke, Jean Boivin, and Piotr Eliasz. Measuring the effects of monetary policy: A factor-augmented vector autoregressive (favar) approach. *The Quarterly Journal of Economics*, 120(1):387–422, 2005. URL `https://EconPapers.repec.org/RePEc:oup:qjecon:v:120:y:2005:i:1:p:387-422`.

Olivier Jean Blanchard and Danny Quah. The dynamic effects of aggregate demand and supply disturbances. *The American Economic Review*, pages 655–673, 1989.

Aaron Chalfin and Justin McCrary. Criminal deterrence: A review of the literature. *Journal of Economic Literature*, 55(1):5–48, March 2017. 10.1257/jel.20141147. URL `https://www.aeaweb.org/articles?id=10.1257/jel.20141147`.

Lawrence J Christiano, Roberto Motto, and Massimo Rostagno. Risk shocks. *American Economic Review*, 104(1):27–65, 2014.

Davide Debortoli, Mario Forni, Luca Gambetti, and Luca Sala. Asymmetric monetary policy tradeoffs. Technical report, 2023.

Eric D Gould, Bruce A Weinberg, and David B Mustard. Crime rates and local labor market opportunities in the united states: 1979–1997. *Review of Economics and statistics*, 84(1): 45–61, 2002.

Steven D Levitt. Understanding why crime fell in the 1990s: Four factors that explain the decline and six that do not. *Journal of Economic perspectives*, 18(1):163–190, 2004.

Ming-Jen Lin. Does unemployment increase crime?: Evidence from us data 1974–2000. *Journal of Human resources*, 43(2):413–436, 2008.

Stephen Machin and Costas Meghir. Crime and economic incentives. *Journal of Human resources*, 39(4):958–979, 2004.

Steven Raphael and Rudolf Winter-Ebmer. Identifying the effect of unemployment on crime. *The journal of law and economics*, 44(1):259–283, 2001.

Frank Smets and Rafael Wouters. Shocks and frictions in us business cycles: A bayesian dsge approach. *American economic review*, 97(3):586–606, 2007.

Tables

A. Aggregate Crime Rates				
Two shocks				
Horizon	Supply	Demand	Monetary	Total
0	15.9	4.5		20.3
5	14.1	8.3		22.4
10	15.9	8.5		24.4
Three shocks				
Horizon	Supply	Demand	Monetary	Total
0	19.3	4.8	3.2	27.3
5	15.9	8.2	8.9	33.0
10	17.3	9.5	8.2	35.0

B. Principal Component of State-Level Crime Rates				
Two shocks				
Horizon	Supply	Demand	Monetary	Total
0	14.5	5.1		19.6
5	12.9	7.4		20.3
10	14.0	8.8		22.8
Three shocks				
Horizon	Supply	Demand	Monetary	Total
0	17.6	5.1	4.3	26.9
5	14.5	7.4	8.3	30.2
10	15.5	9.8	7.8	33.1

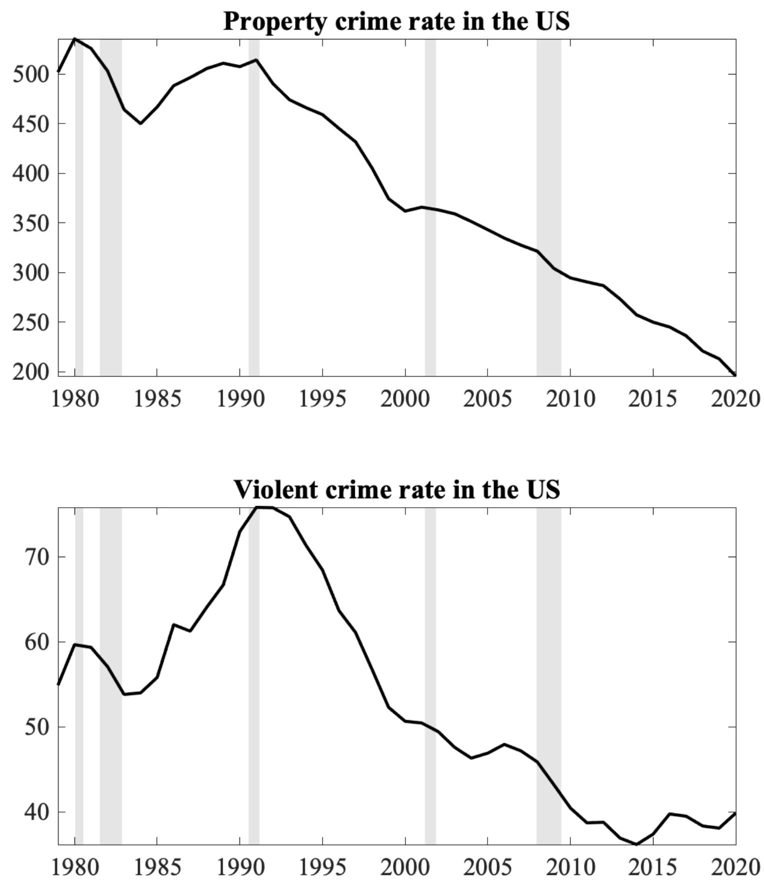
Table 1: Variance decomposition: first principal component

A. Sensitivity			
> 10 crimes per year		No significant effects	
State	Average crimes	State	Average crimes
California	17.5	Alabama	1.8
Colorado	13.5	Arkansas	-1.6
Connecticut	12.0	Georgia	-0.1
Delaware	12.3	Louisiana	-4.6
Massachusetts	15.8	North Carolina	-3.2
Michigan	11.5	Nebraska	0.3
New Hampshire	13.0	New Mexico	-2.2
New Jersey	13.3	Oklahoma	-0.8
Nevada	18.3	South Carolina	-0.6
New York	17.3	Tennessee	-2.1
Rhode Island	12.3	Utah	1.0
Vermont	12.8	West Virginia	1.3

B. Partial correlations of sensitivity		
Variable	Partial Corr	p-value
Unemployment sensitivity	0.55	0.00
Inflation sensitivity	0.42	0.03
GDP	0.09	0.64
Urban population	0.55	0.00
Poverty rate	-0.06	0.76
Population density	-0.06	0.75
Spending to GDP	-0.17	0.39

Table 2: Pane A: Average impulse response functions of crime rates over three years. Column 2 display the states whose responses have at least one significant effects withing within the first 3 years after the shock. Column 4 displays the states whose responses are never significant over the first 3 years. Panel B: Partial correlations between sensitivity (3 years) and other factors.Only 35 states are included in the sample due to CPI availability.

Figures



Notes: The figure plots the US national crime rate per 100,000 inhabitants between 1980 and 2020. The vertical grey areas show periods of recessions.

Figure 1: Crime Rates

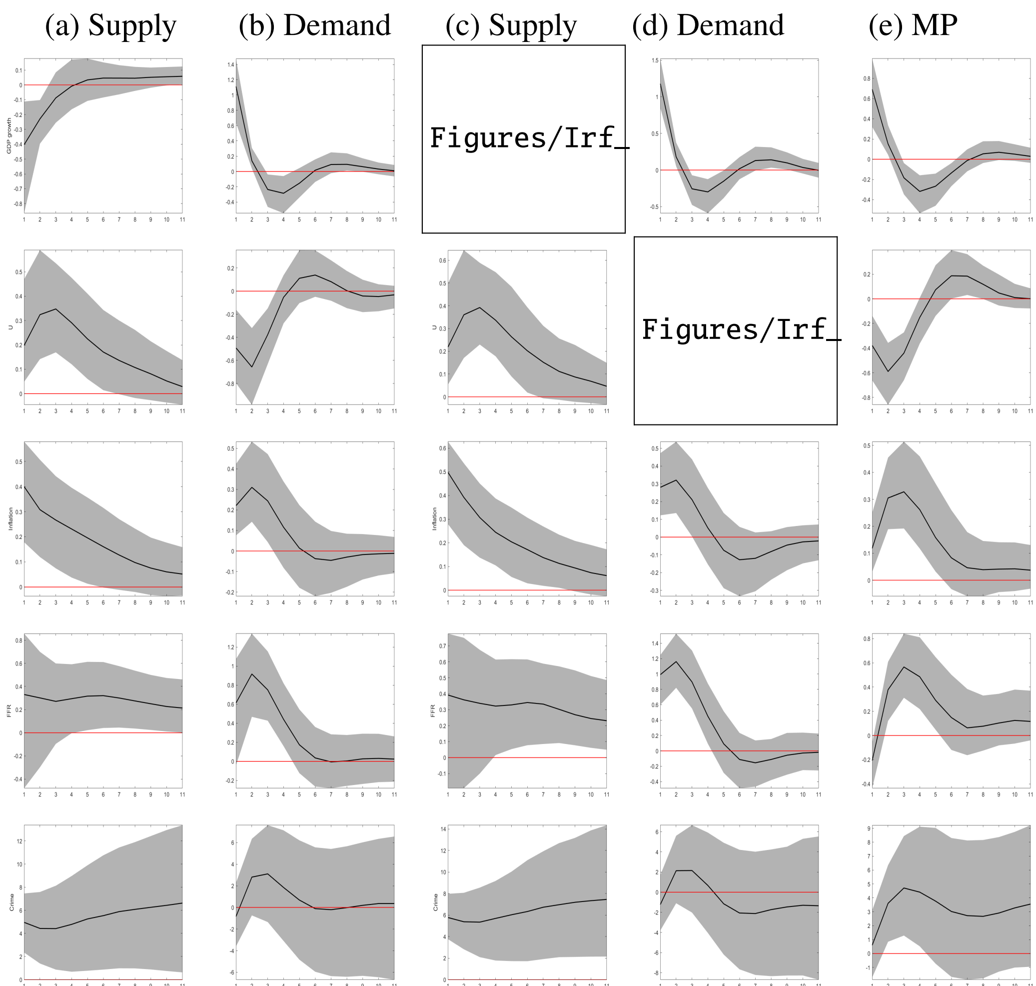


Figure 2: Two.-shock model: supply shock, column (a); demand shock, column (b). Three.-shock model: supply shocks, column (c); non-policy demand shocks, column (d); monetary policy shock, column (e). Dark areas are 68% confidence bands, solid black lines represents the average across all impulse response functions.

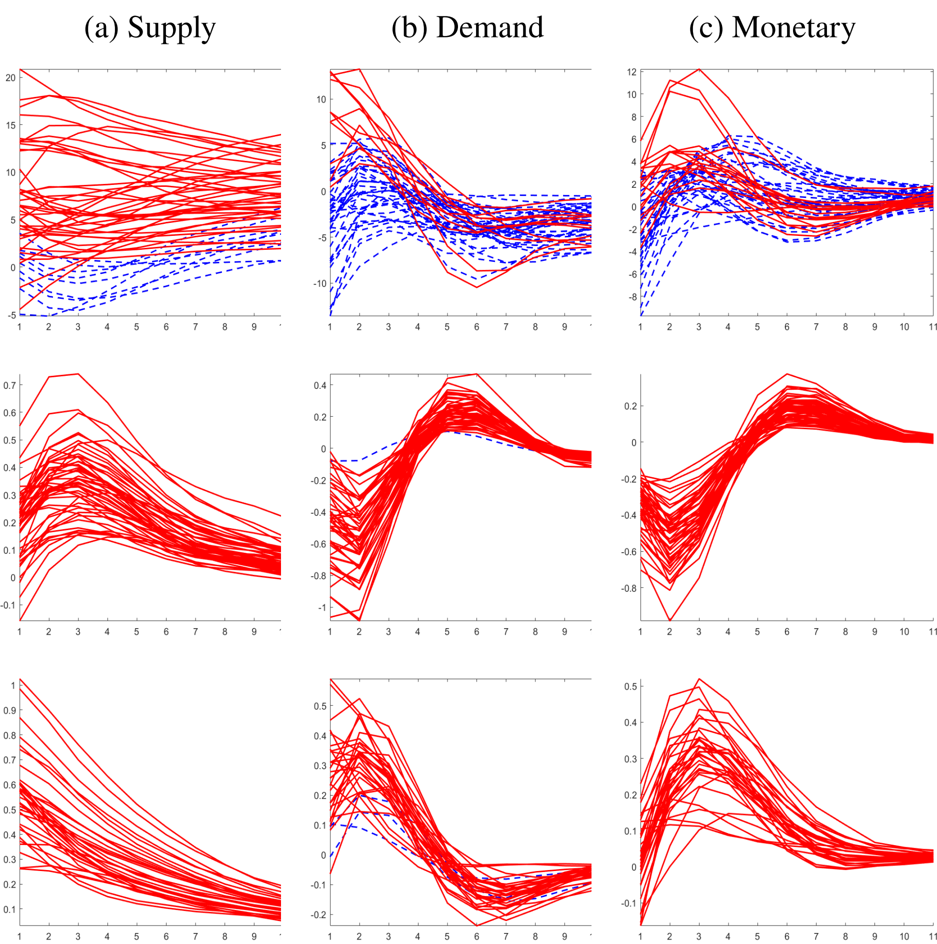


Figure 3: Impulse response functions of state level crime rates (first row) unemployment (second row) and inflation (third row). Solid red lines are the responses with at least one significant coefficient. Dashed blue lines are nonsignificant responses.

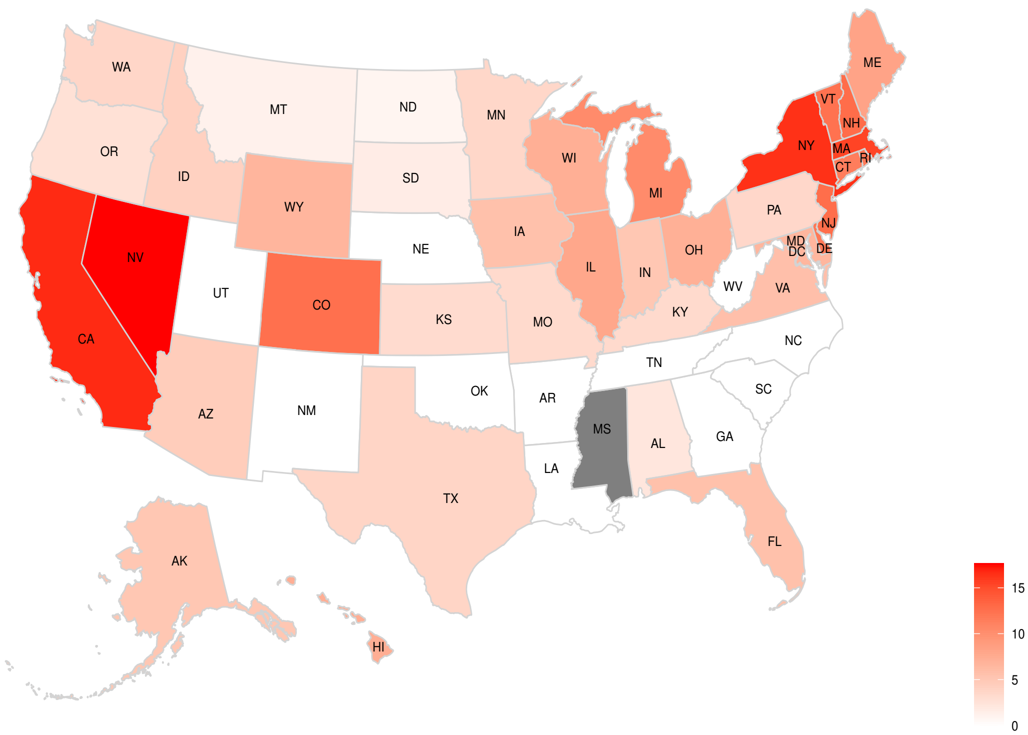


Figure 4: Shock sensitivity by state.

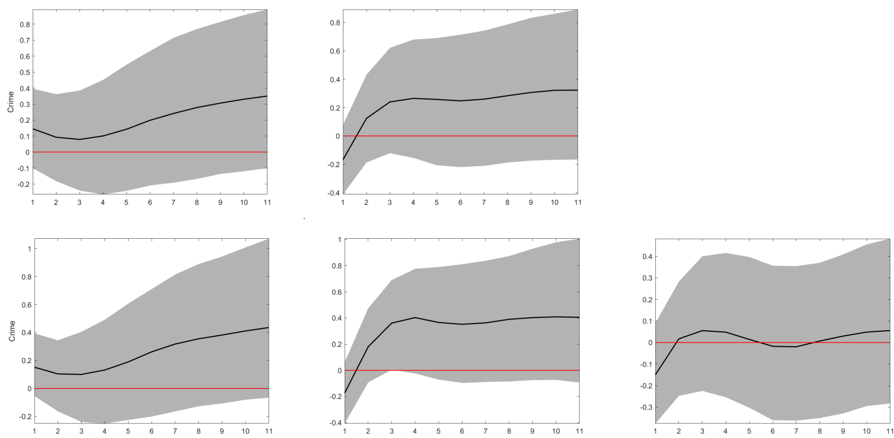
Online Appendix

Variable	Supply		Demand		Monetary policy	
	Partial Corr	p-val	Partial Corr	p-val	Partial Corr	p-val
Unemployment sensitivity	**0.55**	0.00	0.02	0.90	-0.29	0.14
Inflation sensitivity	**0.42**	0.03	-0.23	0.25	-0.23	0.24
GDP	0.09	0.64	-0.19	0.35	-0.02	0.93
Urban population	**0.55**	0.00	**0.56**	0.00	0.08	0.68
Poverty rate	-0.06	0.76	-0.16	0.41	0.05	0.82
Population density	-0.06	0.75	-0.32	0.10	**-0.41**	0.03
Spending to GDP	-0.17	0.39	-0.15	0.44	0.38	0.05

Table 3: Partial correlations between sensitivity (3 years) and other factors.Only 35 states are included in the sample due to CPI availability.

Panel A

(a) Supply (b) Demand (c) Monetary



Panel B

(a) Supply (b) Demand (c) Monetary

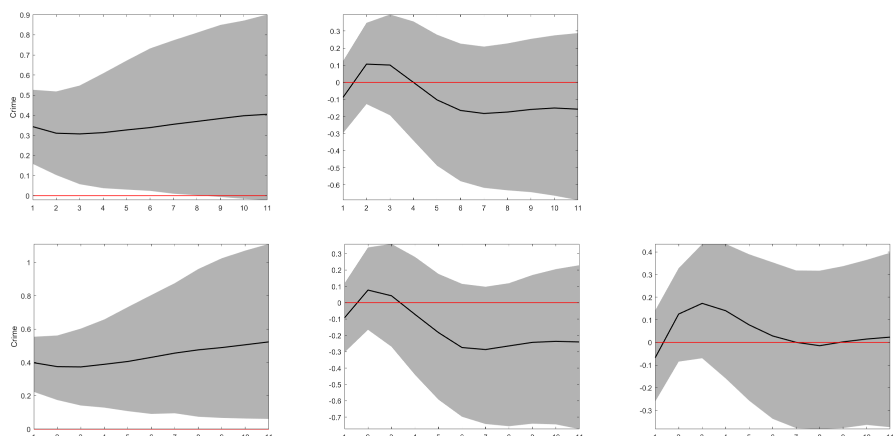


Figure 5: Additional checks. Panel (a): impulse response functions of violent crime (homicides plus aggravated assault) to supply shocks (left column) and demand shocks (middle column) and monetary policy shock (right column). Panel (b): impulse response functions of the first principal component to supply shocks (left column) and demand shocks (middle column) and monetary policy shock (right column). Dark areas are 68% confidence bands, solid black lines represents the average across all impulse response functions.

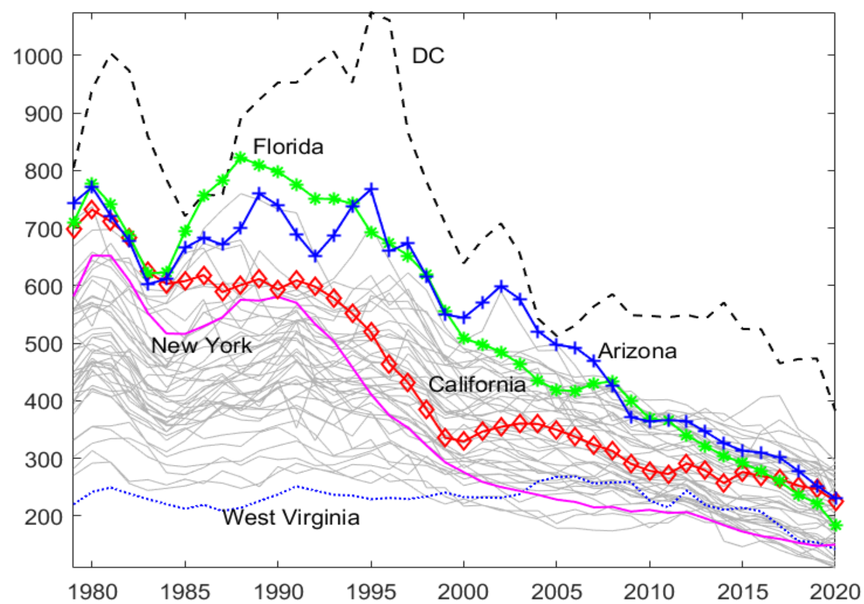


Figure 6: State-level crime rates (property crimes plus robbery).

	(1)		(2)	
	Estimate	t-stat	Estimate	t-stat
ΔU_t	-0.3164		-0.4193	
π_t			0.7795*	
Constant	-2.2905*		-4.3307*	

Table 4: Regressions of aggregate changes in crime rates on unemployment changes and GDP Deflator Inflation.

	(1)		(2)	
	Estimate	t-stat	Estimate	t-stat
ΔU_t	-0.2838		0.5497*	
π_t			3.1692*	

Table 5: Fixed-effects regressions of state-level changes in crime rates on unemployment changes and CPI Inflation.