The Confidence Channel of Macroeconomic Uncertainty: Evidence from Disaggregated IP indices*

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Abstract

This paper evaluates the link between confidence and the transmission of macro uncertainty shocks. Using data on aggregate and disaggregate industrial production (IP) indices, we estimate a factor augmented vector autoregressive model. First, we compute the impulse response functions and find that uncertainty shocks adversely affect total IP, and generate a disproportionate change in disaggregated IP indices. Second, we conduct a counterfactual analysis to evaluate whether changes in consumer confidence amplify the effect of uncertainty shocks on IP indices. Our results suggest that uncertainty shocks propagate through a confidence multiplier effect. Third, we conduct a historical decomposition exercise and find that relative to consumer confidence shocks and shocks to total IP, macro uncertainty shocks contributed the most to the historical changes in total IP during the early 80s recession and the 2008-2009 financial crisis. Last but not least, we employ a historical counterfactual analysis and show that uncertainty shocks propagated via a confidence channel during those two recessions.

Keywords: Uncertainty shocks, confidence channel, transmission, business cycles, FAVAR.
JEL: C32, C53, E32.

1 Introduction

The vast theoretical and empirical literature on uncertainty emphasize that shocks to uncertainty have an adverse effect on economic activity.[1] Yet, little in known on the amplification channels

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[1]See for example Bernanke (1983), McDonald and Siegel (1986), Pindyck (1988), Bloom (2009), Panousi and Papanikolaou (2012), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018).

of uncertainty shocks (see Oh, 2020). Leduc and Liu (2016) reveal that an uncertainty shock can be classified as an aggregate demand shock, and recent work by Angeletos and Lian (2019) show that aggregate demand shocks propagate into the economy through a confidence multiplier effect. Motivated by these findings, we evaluate the empirical relevance of the theoretical proposition by Angeletos and Lian (2019) for the case of uncertainty shocks. In fact, a large literature examines the effect of uncertainty shocks on aggregate economic activity, while another literature studies the effect of consumer confidence on business cycles.[2] Yet, to our knowledge, no empirical work has investigated the link between confidence and the transmission of uncertainty shocks.

This paper studies the effect of macroeconomic (macro) uncertainty shocks on industrial production (IP) and evaluates whether the systematic behavior of confidence has a key role in the propagation of uncertainty shocks to the macroeconomy. Thus, our paper directly contributes to the understanding of the amplification channels of uncertainty shocks (see Oh, 2020). Unlike previous studies that focused on the impact of uncertainty on aggregate economic activity, we rely on aggregate and disaggregate data on IP indices to investigate whether uncertainty shocks alter the composition of aggregate output. Moreover, we inquire whether changes in consumer confidence amplify the effects of uncertainty shocks on sectoral output. Furthermore, we ask whether uncertainty shocks had an economically significant effect on total industrial production during the early 80s recession and the 2008-2009 financial crisis, and assess whether uncertainty shocks propagated via a confidence channel during those two recessions.

Before we proceed any further, it is crucial to explicate the difference between uncertainty and confidence, and the interplay between the two. As discussed in Nowzohour and Stracca (2017) changes in confidence can stem from positive news and/or animal spirits; whereas, uncertainty can

[2] For the literature on uncertainty shocks, see for example Bloom (2009) and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018). For the literature on the effect of confidence shocks, see for example Blanchard (1993) and Barsky and Sims (2012).

be attributed to two types. Type I uncertainty refers to the range of possible future economic prospects, whereas Type II uncertainty refers to the lack of information about the probability distribution from which future economic prospects are drawn. An unexpected increase in either Type I or Type II uncertainty would reduce confidence. For instance, if there is a wide range for the possible economic outlook a year from today (Type I uncertainty), consumers will be less confident about increasing their consumption today because they are very uncertain about their expected future income. Also, when economic players have little information about the probability distribution of possible economic outlooks (Type II uncertainty), they will be unable to form expectations to assess risk; thus, economic players will become highly risk averse and their confidence will drop.

We use the Jurado, Ludvigson, and Ng (2015) - hereafter JLN - measure of uncertainty, which computes the weighted average of the conditional volatility of the unforecastable component for a range of macroeconomic series, for two reasons. First, their measure is in line with theoretical models of uncertainty that imply that uncertainty is an unobservable variable. Second, popular proxies of uncertainty used in existing empirical work such as the stock market volatility, the cross sectional dispersion of productivity, and indices based on textual analysis (e.g. the occurrence of keywords related to uncertainty in news articles) can change over time due to changes in other observable variables that are unrelated to uncertainty such as consumer confidence. The JLN measure, however, exhibits independent variation from consumer confidence and these proxies of uncertainty; thus, it reflects the nontrivial difference between uncertainty and confidence.

In this paper, we estimate a structural factor-augmented vector autoregressive (FAVAR) model that builds on Bernanke, Boivin and Eliasz (2005) and Boivin, Giannoni, and Mihov (2009). Our model comprises of 3 observed factors: macroeconomic uncertainty, consumer confidence, and aggregate industrial production. The unobserved factors are extracted from 293 disaggregated industrial production indices. We first compute impulse response functions and find that aggregate industrial production significantly falls after an unexpected increase in uncertainty. More interestingly, we find important heterogeneity in the responses of disaggregate industrial production indices to an uncertainty shock. In particular, we find that the manufacturing and durable goods sectors tend to be more responsive to uncertainty shocks than other sectors. The heterogeneity in the sectoral responses can be explained through two main channels. The first channel refers to a demand-side channel, which entails that uncertainty leads to a reduction in consumer expenditures on durable goods because these purchases cannot be easily reversed (see Romer, 1990). The second channel refers to a supply-side channel, which states that the reduction in investment spending triggered by uncertainty shocks can damage the productivity of the manufacturing sector (see Disney, Haskell and Heden, 2003).

Then, we evaluate whether uncertainty shocks propagate through a confidence multiplier effect. First, we found that an uncertainty shock significantly damages consumer confidence up to six months after the shock. Second, we conduct a counterfactual analysis by constructing a sequence of hypothetical shocks that leaves the dynamic response of consumer confidence to an uncertainty shock at a zero level across all subsequent periods (see Kilian and Lewis, 2011). We find that the counterfactual responses of both aggregate and some disaggregated industrial production indices lie outside the confidence bands of the actual responses. Thus, our findings reveal that the effect of uncertainty shocks on industrial production are amplified via confidence channel.

Third, we analyze the historical contribution of uncertainty shocks into the changes in industrial production during the 1980-1982 and the 2008-2009 periods. Our interest in the Volcker disinflation period stems from the increase in the volatility of money growth as the Fed was trying to control a poor measure of money (see Keating and Smith, 2019). Moreover, we are interested to contribute to the vast literature on the role of uncertainty shocks in explaining the Great Recession.[3] We found

[3] See Bloom (2014); Baker, Bloom and Davis (2016); Born, Breuer and Elstner (2018).

that uncertainty played an economically important role in the changes of industrial production during those periods. Specifically, our results reveal that for both historical episodes, uncertainty shocks contributed more than consumer confidence and industrial production shocks in explaining the historical changes in industrial production during the Volcker disinflation period and the 2008-2009 financial crisis.

Moreover, we assess the relevance of the confidence channel of uncertainty shocks during the early 80s and 2008-2009 recessions. To pursue this investigation, we compute the historical path that reflects the contribution of uncertainty shocks to the historical changes in industrial production, along with a historical counterfactual path that depicts the contribution of uncertainty shocks to the historical changes in industrial production when consumer confidence remains at its initial level. We found that during both recessions, the historical counterfactual path is smaller than the historical path, which indicates that during those recessions, the effect of uncertainty shocks on industrial production was magnified via a change in consumer confidence.

Our paper is structured as follows. The second section discusses the data that we use. The empirical strategy is presented in section 3. Section 4 discusses the results. In Section 5, we conduct a historical decomposition exercise to study the role of uncertainty shocks in explaining the changes in industrial production during the 1980-1982 period and the Great Recession. Section 6 concludes.

2 Data

In this study, we use data on macroeconomic uncertainty, consumer confidence and industrial production (IP). We measure consumer confidence by the index of consumer expectations by the University of Michigan. We collect data on total IP and 293 disaggregated IP indices by industry from the Federal Reserve Board of Governors and take the difference of the natural logarithm to compute the growth rate of industrial production. Our data spans from 1978:M4 to 2019:M12.

We use the macroeconomic uncertainty index developed by JLN. Unlike the other uncertainty indices in the literature, this index is more correlated with economic activity and changes far more infrequently than the other uncertainty proxies commonly used in the literature (see e.g. Bloom, 2009). In fact, JLN claim that the proxies for uncertainty that are commonly used in the literature are not tightly related to the theoretical models of uncertainty. For instance, one measure used in the literature as a proxy for uncertainty is the stock market volatility. While stock market volatility is observable, this proxy for uncertainty changes due to many different factors that are unrelated to uncertainty, such as changes in leverage, animal spirits, and cross-sectional dispersion in firms levels due to firms' specific business cycles.

The main advantage of the JLN uncertainty index is that first, it removes all the forecastable component of macroeconomic series and then computes the conditional volatility. In fact, apart from JLN, most of the uncertainty measures in the literature are based on the conditional volatility of the raw data, which contains a forecastable component and an unforecastable component. The JLN approach can be summarized as follows. First, we define $U_{jt}^{y}(h)$ as the h, period ahead measure of uncertainty:

$$U_{jt}^{y}(h) = \sqrt{E\left[y_{jt+h} - Ey_{jt+h}|I_t)^2|I_t\right]}. \tag{1}$$

This measure of volatility refers to the conditional volatility of the unforecastable component of variable y_{jt}, where $y_{jt} \in Y_t = (y_{1t}, y_{2t}, y_{Nt})'$. Note that the expectation $E(.|I_t)$ refers to the conditional expectation that economic players make today with respect to the information set I_t available at time t to economic players. To create the macroeconomic uncertainty index, JLN use weights w_j for individual uncertainty measures at each date to construct an aggregate measure for uncertainty:

$$U_t^y(h) = \underset{N\to\infty}{p\lim} \sum_{j=1}^{N} w_j U_{jt}^y(h) = E_w \left[U_{jt}^y(h) \right]. \tag{2}$$

As a result, the JLN macroeconomic uncertainty index is constructed as a measure of the common variation in uncertainty across many series. By construction, this index exhibits independence from other proxies of uncertainty used in the literature that are based on observables.

3 The FAVAR Model

We estimate a factor autoregressive (FAVAR) model that builds on Bernanke et al. (2005) and Boivin et al. (2009) to study the effect of macroeconomic uncertainty on consumer confidence and aggregate and disaggregate industrial production. The key advantage in using the FAVAR model is that it allows computing the impulse responses of a wide range of sectoral industrial production indices to a shock in macroeconomic uncertainty.[4] The main assumption in this model is that the dynamics of a large set of macroeconomic variables are captured by some observed and unobserved common factors. The unobserved factors are extracted from a large set of data on disaggregated industrial production. We formalize the structural FAVAR model where the joint dynamics of observed Y_t, and unobserved factors, F_t, are given by

$$B_0 \begin{bmatrix} Y_t \\ F_t \end{bmatrix} = B(L) \begin{bmatrix} Y_{t-1} \\ F_{t-1} \end{bmatrix} + \varepsilon_t \tag{3}$$

[4] Note that Bernanke et al. (2005), and Forni and Gambetti (2011) have criticized the use of small scale vector autoregressive (VAR) models to identify structural shocks. To conserve the degrees of freedom, traditional VAR models use a small number of variables (i.e. between five to ten variables). In contrast, the federal government and the Fed have access to a large panel of variables that they regularly monitor. Hence, Bernanke et al. (2005), and Forni and Gambetti (2011) argue that the low dimensional VARs are very unlikely to span the large panel of information set used by the policymakers. Furthermore, the inclusion of many variables in VAR models undermines the precision of the model estimates in small samples. Kilian and Lütkepohl (2017) suggest that the extent to which VAR models can be enlarged is limited by the reason that the number of regressors cannot exceed the number of observations. This restriction can be a problem when working with a large dimensional VAR model where the number of parameters increases with the square of the number of variables in the system.

where B_0 represents the matrix of contemporaneous relationships between the variables in the model and ε_t represents a vector of mutually uncorrelated structural shocks.

The reduced form representation of model (1) can be written as follows:

$$\begin{bmatrix} Y_t \\ F_t \end{bmatrix} = \underbrace{B_0^{-1}B(L)}_{A(L)} \begin{bmatrix} Y_{t-1} \\ F_{t-1} \end{bmatrix} + \underbrace{B_0^{-1}\varepsilon_t}_{e_t} \tag{4}$$

where Y_t is a 3×1 vector consists of the log growth of macro uncertainty (U_t), log growth of consumer expectations ($conf_t$), and the log growth of the total industrial production (IP_t). F_t is a $r \times 1$ (where $r = 3$) vector of unobserved factors; $A(L)$ is the matrix of lag polynomials of order $p = 5$;[5]and e_t represents the reduced form residuals such that $e_t \sim N(0, \Omega)$.In the above equation the vector F_t reflects the unobserved factors. Before we estimate equation 2, we need to extract the unobserved factors from a vector of X_t, which consists of industrial production data for 293 disaggregated industries. The observation equation for the system can be written as follows:

$$X_t = \Lambda^y Y_t + \Lambda^f F_t + u_t. \tag{5}$$

where Λ^y is a $N \times 3$ matrix of coefficients on the observable variables, Λ^f is a $N \times r$ matrix of factor loadings, and u_t is a vector of series-specific components that are uncorrelated with the Y_t and F_t. The FAVAR model in equation (4) is estimated using a two-step procedure as in Bovin, Giannoni and Mihov (2009). In the first step, the three unobserved factors are estimated, using the principal components approach by Bai and Ng (2013), from a large dataset X_t. In the second step, we add the estimated factors to the observed variables to estimate a VAR model represented in the equation 2.

[5]We use the Akakie Information Criterion (AIC) to include 5 months of lags in the FAVAR model. See Ivanov and Kilian (2005) on the discussion on selection of the VAR lag order.

In order to identify the structural shocks, and recover the structural parameters in model (3), we use the standard Cholesky decomposition to impose restrictions on the observable variables (Y_t) and the estimated three factors (F_t) in the B_0 matrix .[6] The identification assumptions can be summarized as follows. We follow Caggiano, Castelnuovo, Groshenny (2014) and assume that macro uncertainty (U_t) is predetermined with respect to the other macroeconomic variables in our model.[7] We also assume that consumer confidence ($conf_t$) responds contemporaneously to macro uncertainty (see Nowzohour and Stracca, 2017) and responds to industrial production (IP_t) with a delay of at least one month (see Bachmann and Sims, 2012).[8] Moreover, IP_t is assumed to respond contemporaenously to both U_t and $conf_t$. Similarly, the identification scheme allows the factors (F_t) to respond contemporaneously to innovations in U_t, $conf_t$, and IP_t but the latter only respond with a lag to innovations in the factors. Thus, the factors can be considered as shocks to the U.S. economy that are not captured by uncertainty, consumer confidence and business cycle shocks (see Bernanke et al., 2005 and Boivin,Giannoni and Mihov, 2009).

The effect that confidence has on the transmission of uncertainty shocks on impact can be depicted from the B_0 matrix. Let $b_{0,2,1}$ and $b_{0,3,2}$ reflect the elements from the B_0 matrix that represent the immediate impact response of confidence to uncertainty and the immediate response of total industrial production to confidence, respectively. Then, $b_{0,2,1} \times b_{0,3,2}$ computes the confidence channel of uncertainty shocks on impact, which can be defined as the indirect impact effect of uncertainty on total industrial production. Note that on impact, the direct effect of uncertainty on total industrial production is obtained from the $b_{0,3,1}$ element of the B_0 matrix.

[6] Note that Caggiano, Castelnuovo, Groshenny (2014) argue that the recursive assumption is plausible when monthly data is used to evaluate the effect of uncertainty on other macroeconomic variables.

[7] To evaluate the robustness of our results, we have also estimated the model using a different ordering of the variables. Results not reported herein but available upon request reveal that the results are robust to a different ordering of the variables in the FAVAR model.

[8] Note that Bachmann and Sims have used a trivariate VAR model to evaluate whether government spending shocks propagate to economic activity through a confidence channel. They use Cholesky decomposition to identify the government spending shock and assume that consumer confidence is Wold-causally prior to aggregate output.

Moreover, regardless of whether the indirect impact effect of uncertainty on total industrial production is null, uncertainty shocks can still propagate through a confidence multiplier effect. Specifically, even if $b_{0,2,1} \times b_{0,3,2}$ is equal to zero, if at any other horizon confidence responds to uncertainty shocks, and if the estimated parameters on lagged confidence from the total IP equation are significantly different from zero, then the impulse response of confidence to an uncertainty shock will affect the impulse response of total IP to an uncertainty shock.

Our goal is to disentangle the direct dynamic effect of uncertainty shocks on total IP and disaggregated IP indices from the indirect dynamic effect. The indirect dynamic effect on total IP comprises the impact effect measured by $b_{0,2,1} \times b_{0,3,2}$ and the confidence multiplier effect for subsequent horizons. Thus, to analyze whether a macro uncertainty shock propagates through a change in consumer confidence, we follow Kilian and Lewis (2011) and Bachmann and Sims (2012) and construct a counterfactual analysis to evaluate what would have happened to industrial production, following a shock in macro uncertainty, if consumer confidence remains fixed across all horizons. The confidence multiplier effect associated with uncertainty shocks on total IP and disaggregated IP can be depicted by comparing the counterfactual response with the actual response. We compute the point-wise confidence intervals for the impulse response functions using a residual based wild bootstrap (see Gonçalves and Kilian, 2004 and Yamamoto, 2019). We use 10,000 replications and report the one standard error confidence intervals.

4 The Dynamic Effects of Macro Uncertainty

4.1 The effect of macro uncertainty on industrial production

The solid lines of Figure 1a and Figure 1b report the impulse responses for a 1 percent shock in macro uncertainty on industrial production indices. The 68% confidence intervals computed with a residual wild bootstrap are denoted with shaded regions. We focus on the aggregate and 15 disaggregated industrial production indices. Results for all 293 sectors are reported in the online appendix.[9]

Let us focus first on the response of aggregate industrial production. Following an uncertainty shock, total IP significantly falls by almost 0.208 percent at $h = 4$. We find that the 1-year cumulative effect is -1.438 percentage points. This effect is economically significant, given that the average monthly growth rate in total industrial production is 0.159 percent, which indicates that uncertainty has an important effect on aggregate IP. These findings are in line with the real option value channel,[10] and the financing cost channel,[11] which entail that uncertainty has an adverse effect on aggregate output.

Given that aggregate industrial production is a weighted average of IP indices for different sectors, and to better understand how macroeconomic uncertainty shocks affect aggregate output, we study the dynamic responses of sectoral industrial production indices to a macro uncertainty shock. Figure 1a and Figure 1b reveal important heterogeneity in the responses of sectoral IP, which indicates that macro uncertainty triggers important allocative effects. We find that for almost all industries, industrial production responds negatively to a shock in macro uncertainty. These findings clearly reveal that there is little evidence for the convex marginal revenue channel (see Hartman, 1972 and Abel, 1983), which implies that an increase in uncertainty would increase investment and output.[12] Moreover, our results also show little evidence for the precautionary saving channel (see

[9] The online Appendix is available at: https://sites.google.com/site/mohamadbkaraki/KROnlineAppendix.pdf

[10] The real option value channel states that investors with imperfect information will postpone their investment projects when economic uncertainty increases (see, Bernanke, 1983; McDonald and Siegel, 1986; Pindyck, 1988). There is an option value for delaying investment projects because investors will be able to collect more information in the upcoming periods that can improve investment decision-making.

[11] The financing cost channel also entails that uncertainty has a negative effect on output Panousi and Papanikolaou (2012). Consistent with the agency theory, it is well known that managers own a large fraction of publicly traded companies. Given that managers are not diversified, they often take a risk-averse stance when uncertainty is high. As a result, higher uncertainty will pull away managers from pursuing new investment projects, which will negatively affect economic activity.

[12] Hartman (1972) used a discrete time model of investment decision for a risk neutral firm that operates in a

Leland, 1968), which states that the effect of uncertainty on output is ambiguous.[13]

We find that durable goods industries are far more damaged than nondurable goods industries. For instance, we find that an uncertainty shock triggers an economically significant decrease in motor vehicle body and trailer, and motor homes. Furthermore, our results reveal that uncertainty shocks damage the furniture and related production, the household appliance and the computer and electronic products sectors. This result is consistent with the demand side channel of uncertainty proposed by Romer (1990), which implies that higher uncertainty lowers consumer spending on irreversible purchases. Overall, our findings imply that industrial production for the manufacturing sector falls the most following an unexpected increase in uncertainty. For instance, in absolute terms, the 1-year cumulative response of manufacturing is more than four times the response of mining (excluding oil and gas). This finding is in line with Disney, Haskell, and Heden (2003), who argue that uncertainty shocks adversely affect productivity in the manufacturing sector due to the fall in investment spending. Our results also show that uncertainty shocks affect nondurable goods industries. For instance, the food, and the beverage and tobacco industries respond negatively to an uncertainty shock. Regarding industries within the agricultural sector, we find that dairy products and grain and oilseed milling are largely unaffected. Interestingly, we find that an uncertainty shock triggers an increase in hydroelectric power generation.

Overall our findings reveal that macro uncertainty has an adverse effect on both aggregate and disaggregate industrial production indices. These findings indicate that the negative impact

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competitive market and faces convex adjustment costs. His model implies that if the marginal revenue product of capital is a strictly convex function of output prices, then investment and economic activity will increase as uncertainty about the price of goods increases. Later Abel (1983) built on Hartman (1972) and used a continuous time model of investment. His model implies that regardless of the curvature of the cost functions, an increase in output price uncertainty will tend to increase investment and output if the marginal revenue product of capital is a strictly convex function of output prices.

[13]The precautionary saving channels states that given that most people are risk averse, an increase in uncertainty will lead to an increase in precautionary saving (see Leland, 1968). This increase in saving will trigger an increase in investment but also a reduction in consumption. As a result, based on this channel, the final effect of uncertainty shocks on output is ambiguous.

that uncertainty has on total industrial production is not an artifact of an aggregation problem. Moreover, our results at the disaggregated level reveal that the combined quantitative effect of the real option value channel and the financing cost channel is larger than the effect of the precautionary saving channel and the convex marginal revenue channel. Moreover, our findings point that uncertainty shocks have significant allocative effects.

4.2 The effect of macro uncertainty on consumer confidence

Figure 2 reveals that the response of consumer confidence to a positive shock in macroeconomic uncertainty is significantly negative at short horizons ($h = 0 - 5$). Following a 1 percent increase in uncertainty shocks, consumer confidence drops by 0.2 percent three months after the shock. Our results reveal that uncertainty adversely affects consumer confidence in the short-run. These findings are in line with the theoretical reasoning by Nowzohour and Stracca (2017) who claim that an increase in uncertainty, that stems from a broader range of possible economic prospects and/or a lack of information about the probability distribution of future economic prospects, will negatively affect consumer confidence.

4.3 Does consumer confidence amplify the effect of a shock to macro uncertainty?

The theoretical propositions by Angeletos and Lian (2019) imply that aggregate demand shocks propagate into the economy through a confidence multiplier effect. Given that work by Leduc and Liu (2016) found that uncertainty shocks resemble aggregate demand shocks, we evaluate in this section the empirical relevance of the theoretical propositions by Angeletos and Lian (2019) to the case of uncertainty shocks.

Figure 3a and Figure 3b plot the actual responses of aggregate and disaggregate industrial production indices with their respective confidence bands, along with the counterfactual response. The figures illustrate that for all horizons, the solid line is always larger than the dashed line. In other words, the reduction in total industrial production following a macro uncertainty shock is smaller when consumer confidence is held constant. This result indicates that the effect of macro uncertainty on industrial production is amplified by the change in consumer confidence. To better detect the differences in the responses, we define the confidence wedge as the difference between the 1-year cumulative actual response and the 1-year counterfactual response (see Table 1). For total industrial production, we find that the confidence wedge is -0.428 percentage points. This result is economically significant, given that the average monthly growth rate of total industrial production is 0.151 percent.

To evaluate the relevance of the confidence channel at the industry level, we compute the counterfactual responses for disaggregated industrial production indices and compare those with the actual responses and their respective confidence bands. For almost all sectors, Figure 3a and 3b reveal that following an uncertainty shock, the decline in the actual responses of IP is larger than the one depicted for the counterfactuals. Moreover, the counterfactual responses are smaller than the upper bound of the confidence band for the actual responses for manufacturing, machinery, furniture and related products, and computer and electronic products. Interestingly, we find important heterogeneity in the confidence multiplier effect associated with uncertainty shocks across industries. For instance, Table 1 reveals that the 1-year confidence wedge is -0.478 percentage points for manufacturing (NAICS). Also, we find that the 1-year confidence wedge is -0.282 and -0.199 percentage points for durable goods and nondurables, respectively.

Overall, our results point that the effect of uncertainty shocks on industrial production is amplified via a confidence channel. These findings are supported at both aggregate and disaggregated level. The industries that are subject to the confidence channel constitute more than 12 percent of

GDP.

4.4 Historical decomposition

In this section, we conduct a historical decomposition exercise to investigate the contribution of uncertainty shocks to the change in total industrial production during the 1980-1982 period and the 2008-2009 financial crisis. Our interest in studying these episodes stems from two reasons. First, during those episodes, the U.S. has experienced the worst two recessions since World War II. Second, as found by JLN, the 1981-1982 and the 2008-2009 periods are two major episodes of macroeconomic uncertainty. How does a shock in uncertainty compare to other structural shocks in the system in explaining the historical change in industrial production? To pursue this investigation we construct the historical decomposition as follows:

$$\begin{bmatrix} \widehat{Y}_t \\ \\ \widehat{F}_t \end{bmatrix} \approx \sum_{i=0}^{t-1} \widehat{\Theta}_i \widehat{v}_{t-i} \tag{6}$$

where $\widehat{Y}_t$ and $\widehat{F}_t$ denote, respectively, the 3×1 and 3×1 vectors of fitted aggregate variables and estimated factors of the $FAVAR$, $\widehat{\Theta}_i$ denotes the matrix of estimated structural impulse responses at lags $i = 0, 1, 2, ...$ and $\widehat{v}_{t-i}$ is a vector of estimated structural shocks. As we are interested in the cumulative contribution of macro uncertainty shocks to the variation in industrial production, we focus on the third element of $\widehat{Y}_t$ denoted as $\widehat{Y}_{3t}$,which represents the industrial production.

Figure 4 reports the cumulative contribution of macro uncertainty shocks, consumer confidence shocks and an industrial production shock (i.e. a residual shock) to changes in industrial production. Table 2a and 2b report these cumulative contributions for the two historical episodes that we study. Our results reveal that compared to consumer confidence shocks and shocks to industrial production, uncertainty shocks contributed the most into the changes in industrial production for almost all of the 1980-1981 period (see Table 2a). For the 2008-2009 financial crisis, we found that almost for the entire recession period, a shock in macro uncertainty contributed the most to the historical change of industrial production compared to a consumer confidence shock and a shock to industrial production (see Table 2b). Interestingly, we find that in the aftermath of the financial crisis, uncertainty shocks continued to play an important role in explaining the historical variation of industrial production.

4.5 The propagation of uncertainty shocks during recessions

We now inquire whether the effect of uncertainty shocks on industrial production was amplified through a change in consumer confidence during the early 1980s recession and the 2008-2009 financial crisis. In other words, we ask whether uncertainty shocks propagated through a change in consumer confidence during these two recessions. To pursue this inquiry, we follow Kilian and Lütkepohl (2017) and construct the historical path IP_τ at time τ for the contribution of macro uncertainty shocks to total industrial production, which we define as:

$$IP_\tau = \sum_{i=0}^{t-1} \widehat{\Theta}_i^{un} \widehat{v}_{t-i}. \tag{7}$$

Similarly, the counterfactual historical path $IP_{\tau,c}$ at time τ refers to the contribution of macro uncertainty shocks to total industrial production assuming that consumer confidence remains unchanged following a macro uncertainty shock. This path can be written as follows:

$$IP_{\tau,c} = \sum_{i=0}^{t-1} \widehat{\Theta}_{i,c}^{un} \widehat{v}_{t-i}. \tag{8}$$

Our results in Figure 5 reveals that IP_τ is almost always larger than $IP_{\tau,c}$. Moreover, the wedge between the two paths becomes larger during the 1981-1982 recession and towards the end of the

Great Recession. These findings reveal that the impact of uncertainty shocks on IP during the most severe recessions since the 1970s was amplified via a confidence channel.

5 Conclusion

This paper investigated the link between confidence and the transmission of macro uncertainty shocks. We used data on aggregate and disaggregate industrial production indices and estimated a FAVAR model. First, our results revealed that an increase in uncertainty negatively affects industrial production. Moreover, we found that uncertainty alter the composition of aggregate industrial production. Our findings showed that uncertainty affects durable goods industries more than nondurables. These findings could possibly be explained by the reduction in consumer spending on irreversible purchases. We also found that manufacturing industries are damaged more than other industries upon an unexpected increase in uncertainty. In terms of transmission channels, our results imply that the combined effect of the real option value channel and the financing cost channel dominates the effects drawn from the precautionary saving channel and the convex marginal revenue channel.

Second, we evaluated whether confidence is a potential amplification channel of uncertainty shocks. This investigation is motivated by Angeletos and Lian (2019) who proposed that aggregate demand shocks propagate through a confidence multiplier effect, and Leduc and Liu (2016) who found that uncertainty shocks resemble aggregate demand shocks. To assess the relevance of this confidence channel, we conducted a counterfactual analysis. Our results reveal that for total IP and most disaggregated IP indices, the counterfactual response is smaller than the actual response. More importantly, for total IP and several disaggregate IP indices, the counterfactual response is smaller than the upper bound of the confidence intervals. These findings indicate that uncertainty shocks are amplified via a confidence channel.

Third, we conducted a historical decomposition exercise to study the contribution of uncertainty shocks to the historical change in industrial production during the 1980-82 and 2007-2009 periods. Our results showed that compared to consumer confidence shocks and shocks to industrial production, uncertainty shocks contributed the most to the changes in industrial production for most of the 1980-1981 period. For the Great Recession, we found that for almost the entire recession period, uncertainty shocks contributed the most into the historical change of industrial production compared to consumer confidence shocks and the residuals shocks.

Finally, we inquired on whether the effect of uncertainty shocks on industrial production was amplified through a change in consumer confidence during the early 80s and 2008-2009 recessions. To pursue this investigation, we computed the historical path of industrial production to an uncertainty shock and the historical counterfactual path where consumer confidence is held constant. We found that the effect of uncertainty shocks was amplified via a confidence channel during both recessions.

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Table 1: The 1-year confidence wedge

Sectors	Confidence wedge
Total Industrial Production	-0.428
Manufacturing	-0.478
Durable Consumer Goods	-0.282
Nondurable consumer goods	-0.199
Mining excluding oil and gas	-0.100
Machinery	-0.323
Motor vehicle body and trailer	-0.252
Furniture and related products	-0.321
Household appliance	-0.172
Motor home	-0.209
Computer and electronic products	-0.278
Food	-0.118
Beverage and tobacco products	-0.124
Grain and oil seed milling	-0.041
Dairy Products	-0.043
Hydroelectric power generation	0.046

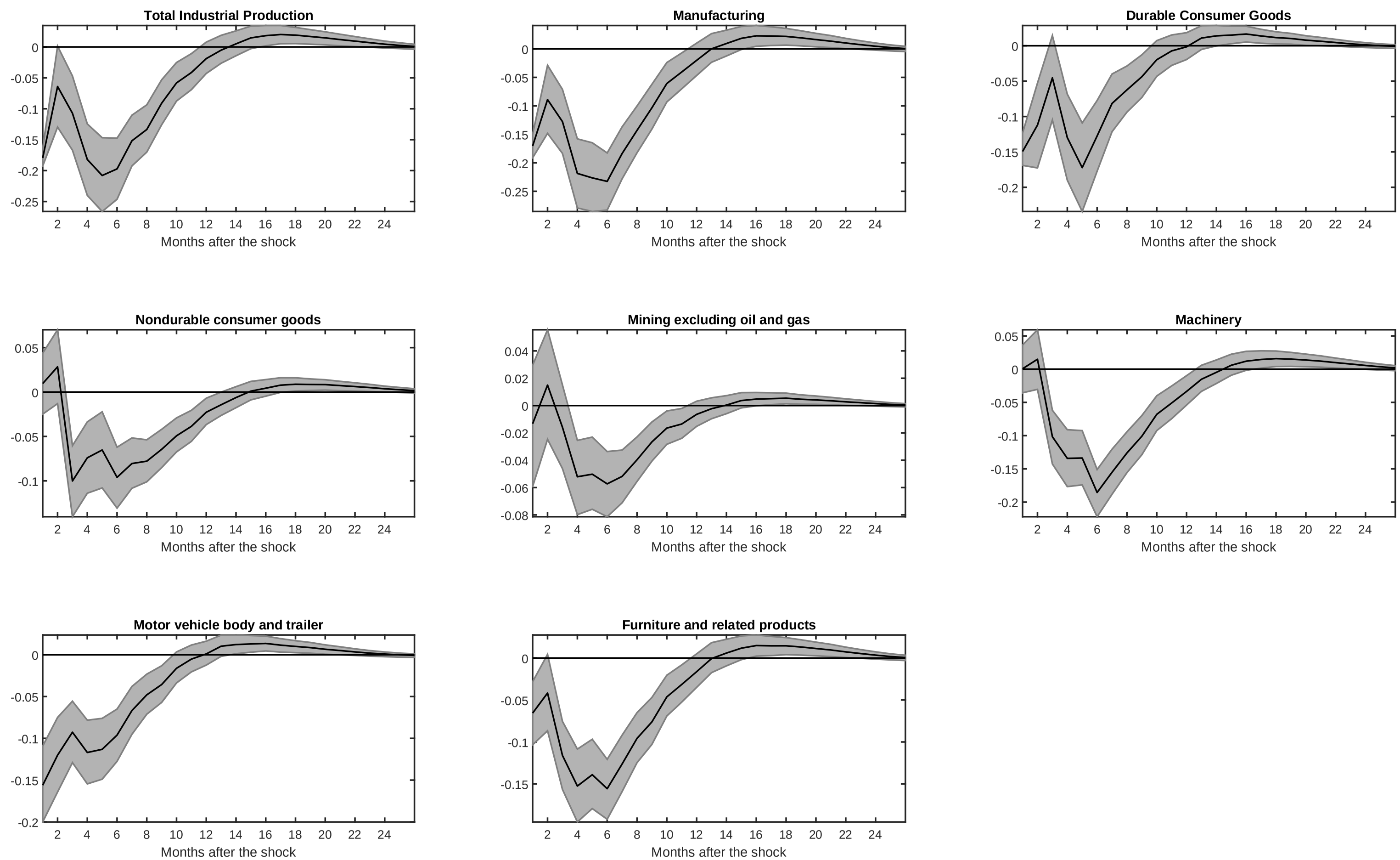
Table 2a: Historical Decomposition during the 1980-1982 period

Date	Cumulative effect of macro uncertainty shocks	Cumulative effect of consumer confidence shocks	Cumulative effect of total IP shocks
1980M1	-0.425	-0.096	-0.685
1980M2	-0.512	-0.081	0.154
1980M3	-0.783	-0.182	-0.057
1980M4	-0.797	0.114	-0.430
1980M5	-0.947	0.084	-0.341
1980M6	-1.106	-0.313	-2.198
1980M7	-0.724	-0.250	-1.350
1980M8	-0.900	-0.262	-0.225
1980M9	-0.968	0.421	-0.566
1980M10	-0.457	0.228	0.762
1980M11	-0.181	0.420	0.948
1980M12	-0.032	0.582	0.195
1981M1	0.021	0.459	0.810
1981M2	0.034	0.538	-0.579
1981M3	0.103	-0.197	-1.070
1981M4	0.051	0.210	-0.760
1981M5	0.111	-0.152	0.650
1981M6	-0.076	0.292	-1.006
1981M7	0.132	0.271	0.099
1981M8	0.023	0.458	-0.563
1981M9	0.176	0.415	0.678
1981M10	0.077	0.051	-0.332
1981M11	-0.071	0.100	-1.211
1981M12	0.214	0.062	-1.094
1982M1	0.068	-0.052	-1.450
1982M2	-0.020	-0.354	-1.189
1982M3	-0.160	-0.301	-2.164
1982M4	0.102	0.035	3.227
1982M5	0.260	-0.023	-1.455
1982M6	-0.099	-0.215	-1.402
1982M7	-0.024	-0.218	-1.228
1982M8	0.184	-0.208	-0.334
1982M9	0.287	-0.127	-0.356
1982M10	0.294	-0.269	-0.666
1982M11	0.153	-0.190	-0.677
1982M12	0.205	0.121	-1.502

Table 2b: Historical Decomposition during the 2008-2010 period

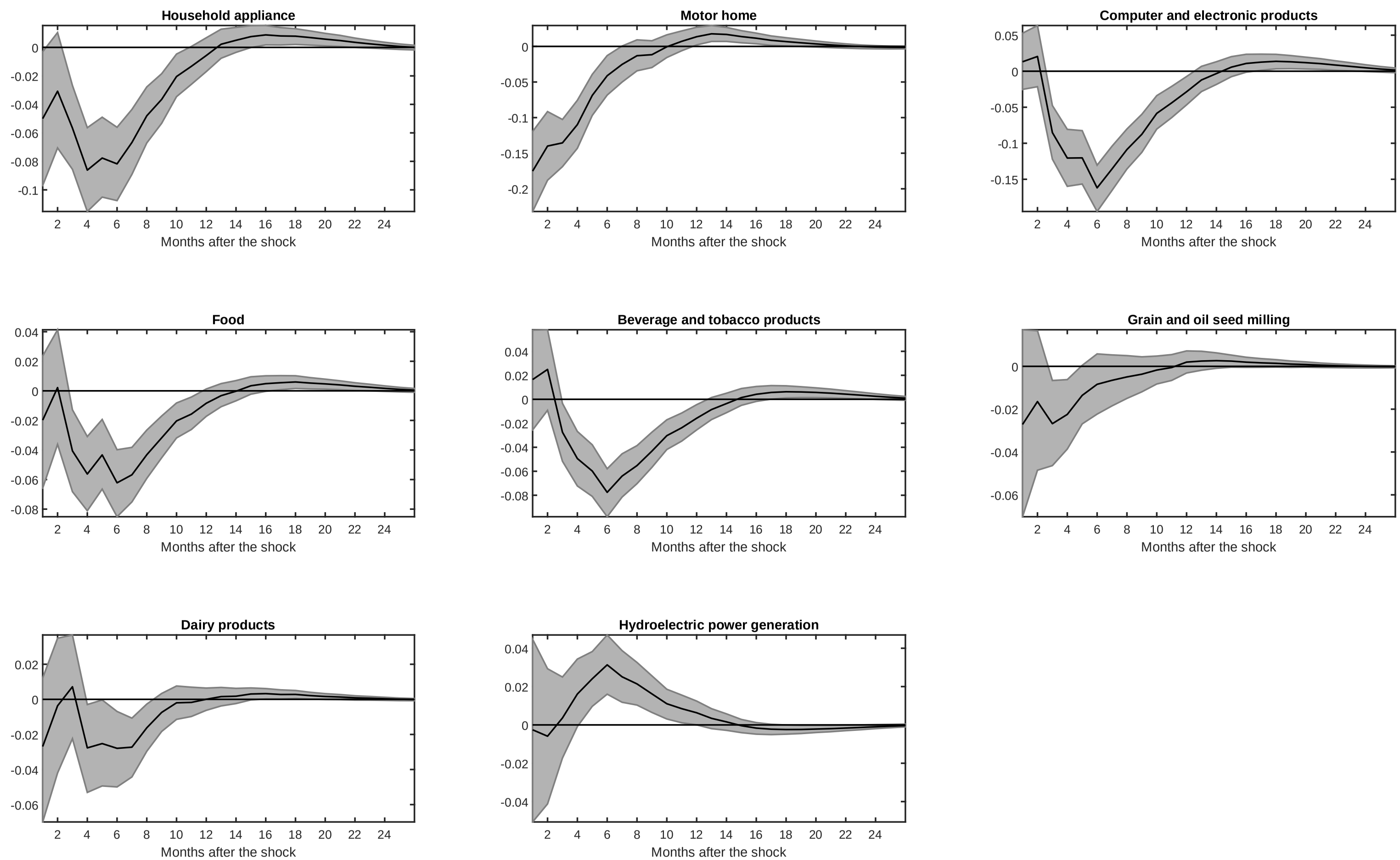
Date	Cumulative effect of macro uncertainty shocks	Cumulative effect of consumer confidence shocks	Cumulative effect of total IP shocks
2008M1	-0.436	-0.231	1.011
2008M2	-0.361	-0.212	0.321
2008M3	-0.314	-0.313	-0.069
2008M4	-0.432	-0.271	-0.319
2008M5	-0.390	-0.325	0.379
2008M6	-0.597	-0.380	-0.939
2008M7	-0.579	-0.617	0.061
2008M8	-0.628	-0.542	0.318
2008M9	-0.821	-0.615	0.016
2008M10	-1.125	-0.344	-1.187
2008M11	-1.297	-0.176	-5.474
2008M12	-1.271	0.233	0.829
2009M1	-1.113	0.023	-0.338
2009M2	-1.309	0.024	-2.058
2009M3	-1.084	-0.245	-0.310
2009M4	-0.772	0.006	0.613
2009M5	-0.345	-0.185	0.170
2009M6	-0.222	-0.240	-0.626
2009M7	0.068	-0.009	-0.214
2009M8	0.258	0.243	-0.552
2009M9	0.385	0.228	1.645
2009M10	0.560	-0.130	1.254
2009M11	0.465	-0.014	0.229
2009M12	0.534	0.121	0.316
2010M1	0.617	-0.066	0.052
2010M2	0.523	-0.118	0.182
2010M3	0.566	-0.149	0.938

Figure 1a: The Response of Industrial Production to a Shock in Macro Uncertainty



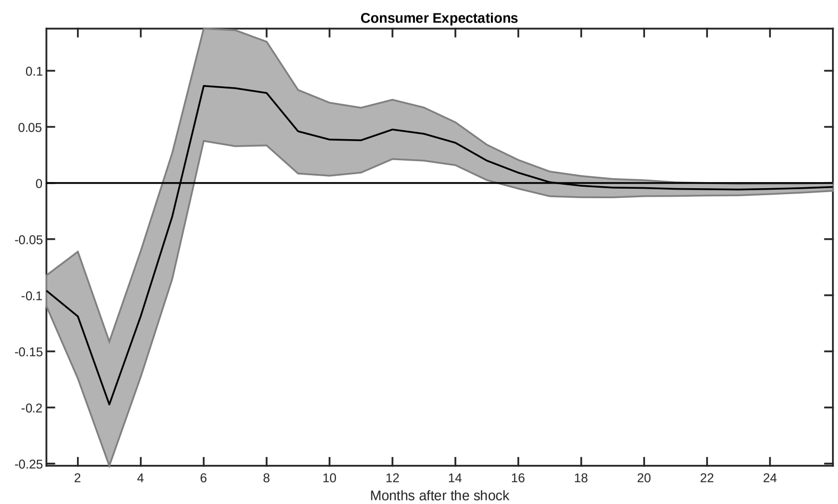
Note: The point estimate is denoted by the solid black line while the shaded regions represent the 68% confidence intervals. The confidence bands are constructed using a residual based wild bootstrap (see Gonçalves and Kilian, 2004).

Figure 1b: The Response of Industrial Production to a Shock in Macro Uncertainty



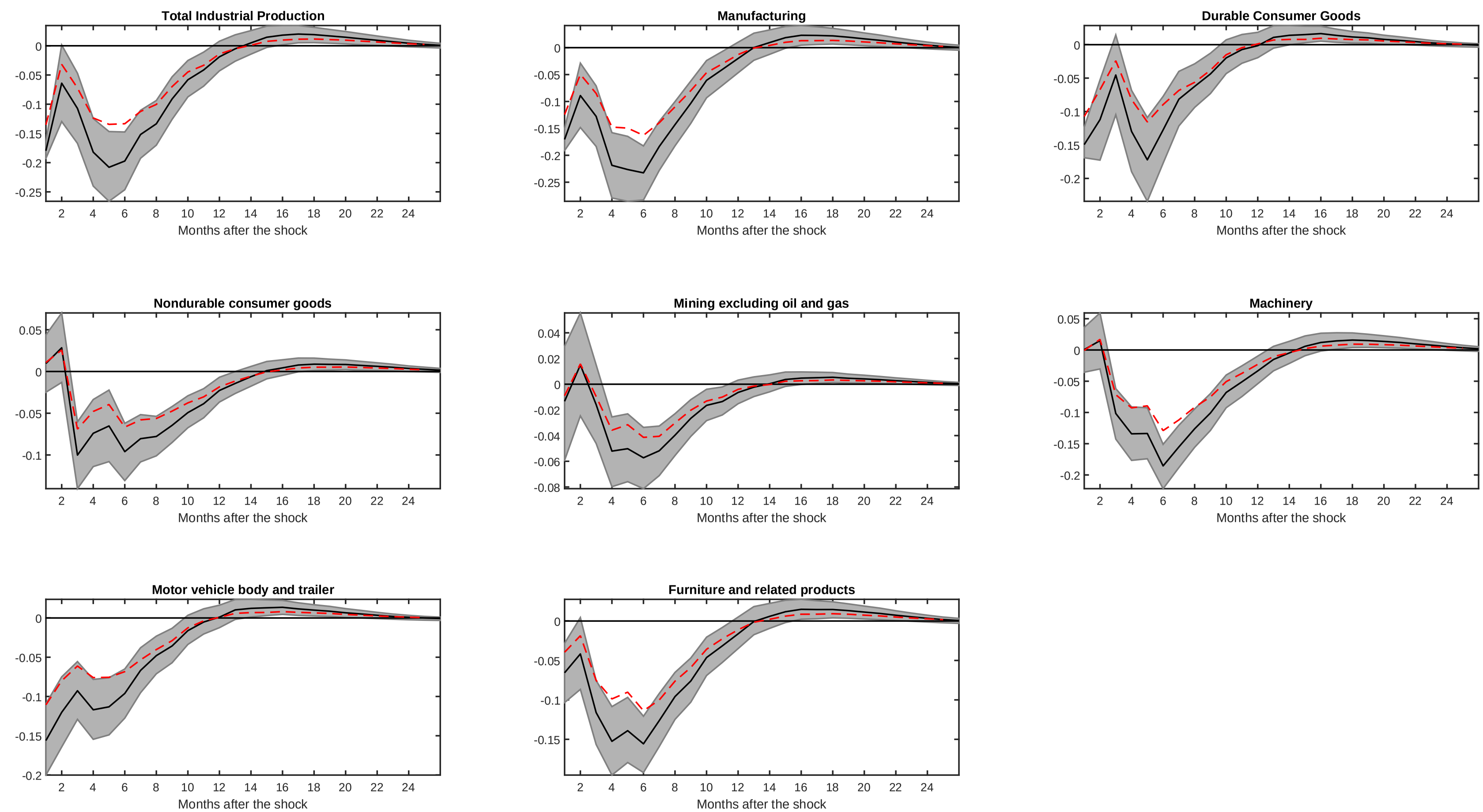
Note: The point estimate is denoted by the solid black line while the shaded regions represent the 68% confidence intervals. The confidence bands are constructed using a residual based wild bootstrap (see Gonçalves and Kilian, 2004).

Figure 2: The Response of Consumer Expectations to a Shock in Macro Uncertainty



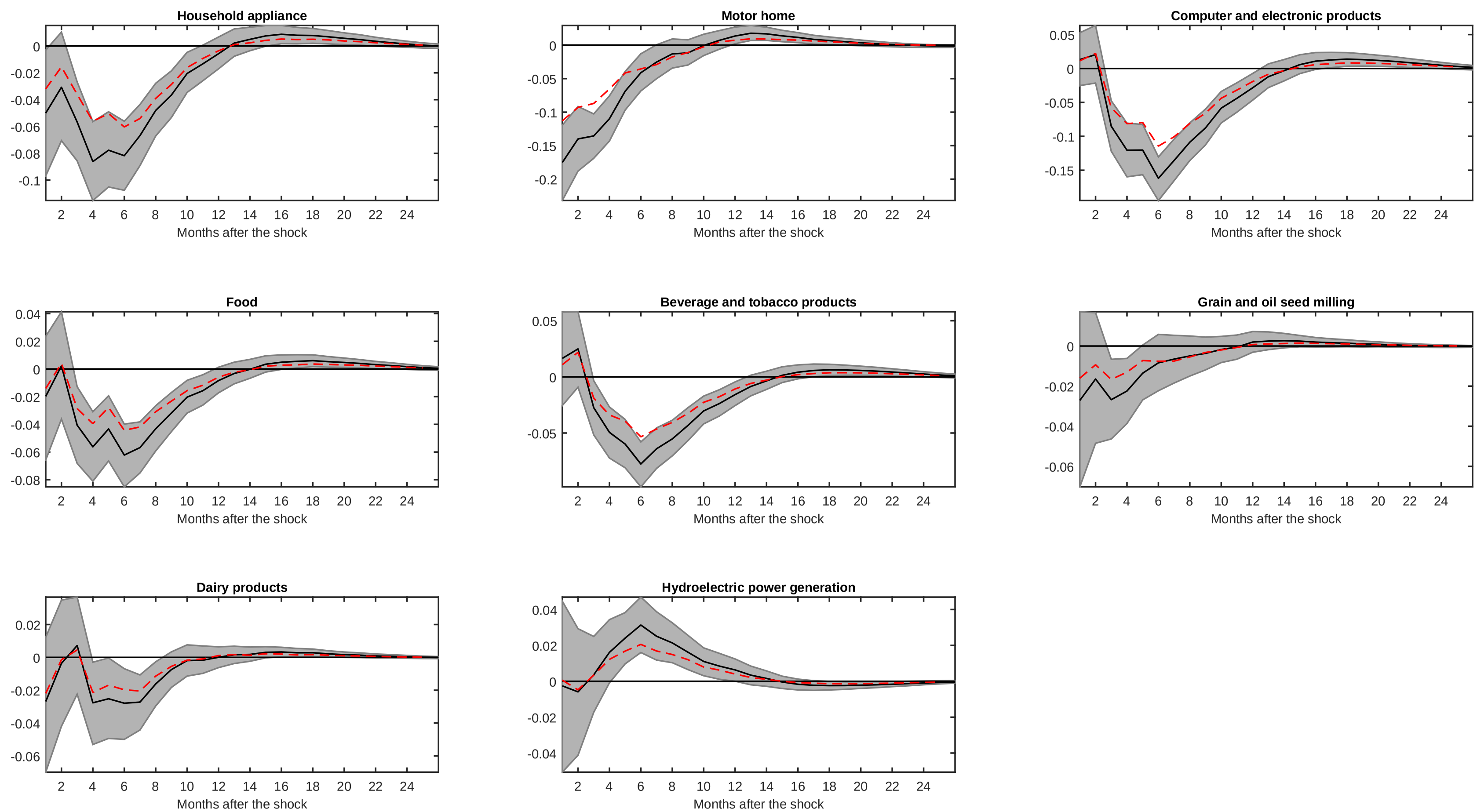
Note: The point estimate is denoted by the solid black line while the shaded regions represent the 68% confidence intervals. The confidence bands are constructed using a residual based wild bootstrap (see Gonçalves and Kilian, 2004).

Figure 3a: The Actual and Counterfactual Responses of Industrial Production to a Shock in Macro Uncertainty



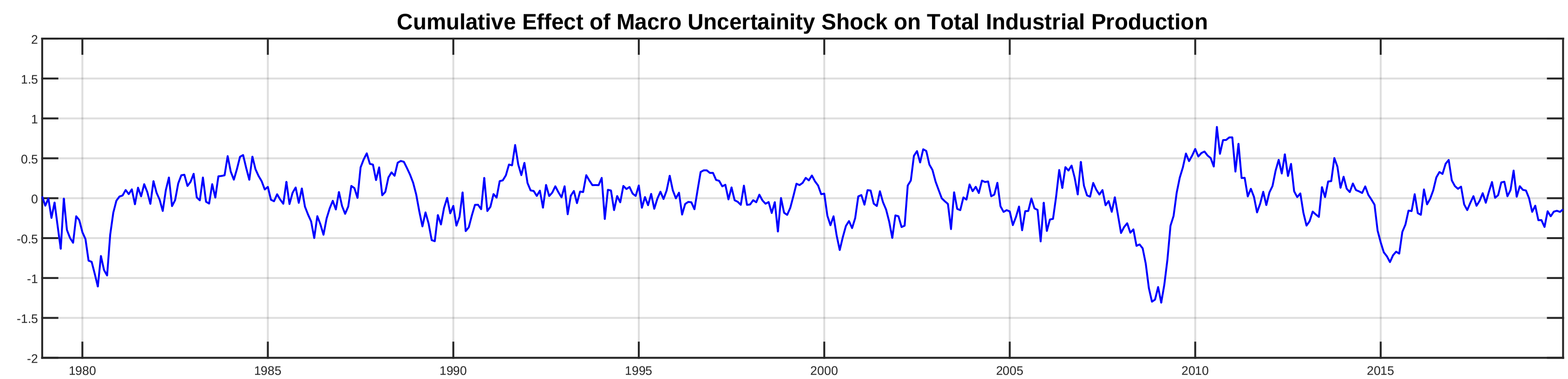
Note: The dashed red line represents the counterfactual response and the black line represents the actual response while the shaded regions represent the 68% confidence intervals. The confidence bands are constructed using a residual based wild bootstrap (see Gonçalves and Kilian, 2004).

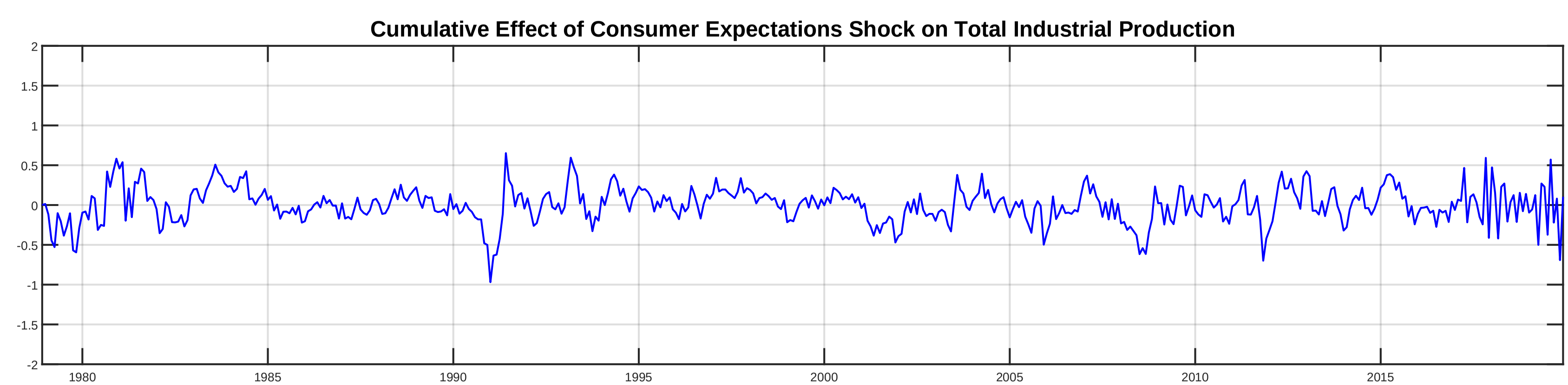
Figure 3b: The Actual and Counterfactual Responses of Industrial Production to a Shock in Macro Uncertainty



Note: The dashed red line represents the counterfactual response and the black line represents the actual response while the shaded regions represent the 68% confidence intervals. The confidence bands are constructed using a residual based wild bootstrap (see Gonçalves and Kilian, 2004)

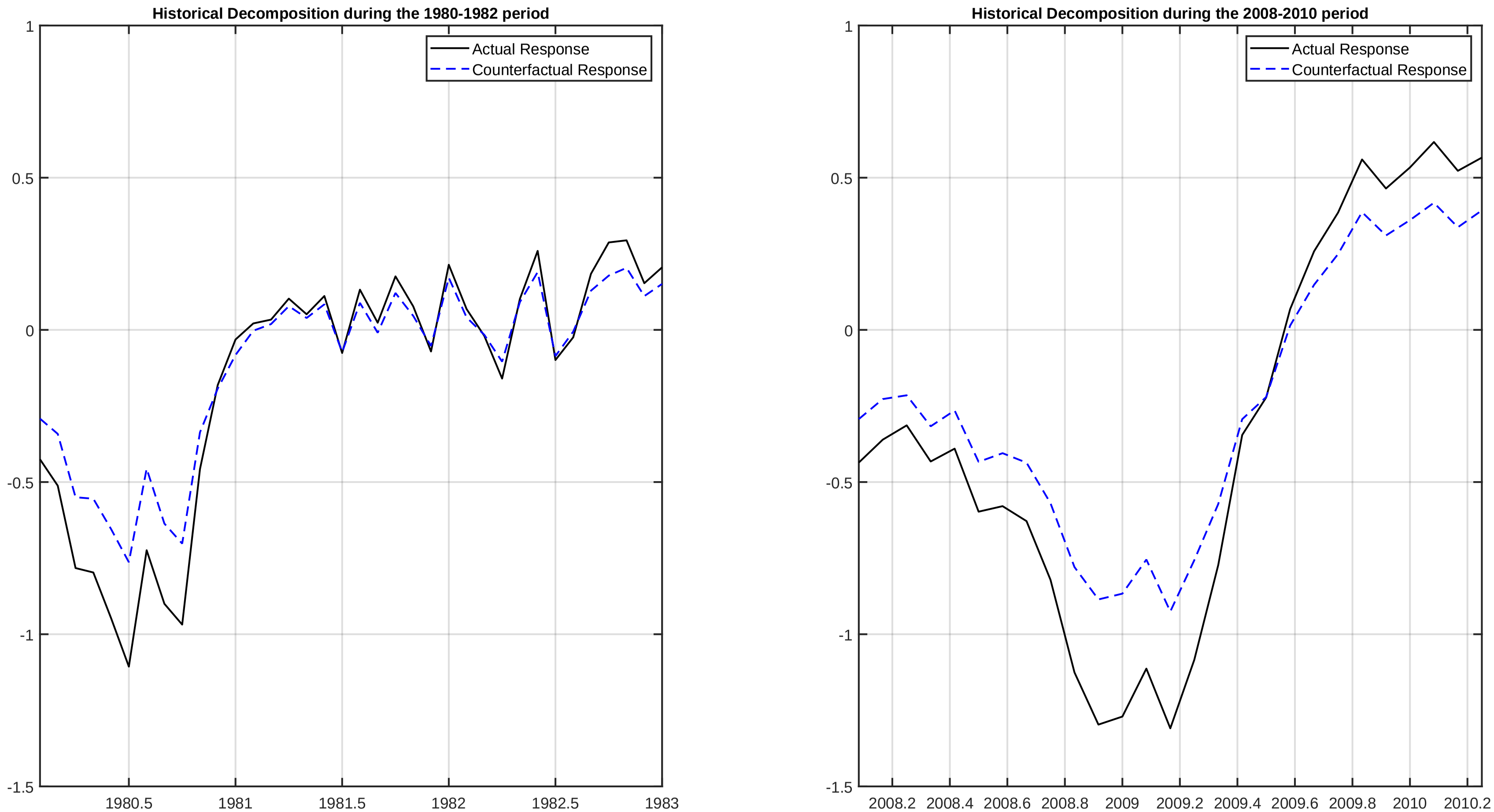
Figure 4: Historical Decomposition of Total Industrial Production





Note: This figure reports the cumulative contributions of macro uncertainty shocks and consumer confidence shocks to total industrial production.

Figure 5: Historical Counterfactual for Total Industrial Production



Note: The solid black line reports the cumulative contributions of macro uncertainty based on eq.(7) and the dashed blue line reports the cumulative contributions of macro uncertainty based on eq.(8).