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Abstract

John Maynard Keynes composed The General Theory as a response to the Great Crash and Great Depression with all their devastating consequences for the US macro economy and financial markets, as well as the rest of the world. The role of expectations his new theory set out has been widely accepted. The role of "animal spirits" he proscribed (i.e. the role of emotion in cognition) has remained much more controversial. We analyse over two million digitally stored news articles from The Wall St Journal to construct a sentiment series that we use to measure the role of emotion at the time Keynes wrote. An eight variable vector error correction model is then used to identify shocks to sentiment that are orthogonal to the fundamentals of the economy. We show that the identified "pure" sentiment shocks do have statistically and economically significant effects on output, money supply (M2), and the stock market for periods of the 1920s.

JEL; D89, E32, E70, N1, N3

Keywords; Great Depression, General Theory, Algorithmic Text Analysis, Behavioural Economics

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1 Introduction

Did sentiment play a role in the 1920s boom and the 1930s depression, and if so, how did these sentiments behave? The US economy was dynamic but highly turbulent at the beginning of the twentieth century[1], with dramatic growth expansions accompanied by credit expansion and stock price surges, but also recurrent recessions. The 1920s economic and stock market boom and the Depression of the early 1930s, gave rise to a need for new ideas in economics to explain the events that had befallen the US and Global economy. The 1930s were thus a nascent period for new economic theories set against the vivid back drop of a US stock market that had fallen by 90% from 1929-1932 and a real economic recession that was comparable in size, although not the largest, to the worst recessions in prior US history dating as far back as the Articles of Association.

In the US, numerous economists such as Benjamin Graham and David Dodd (Graham and Dodd, 1934) lamented the exuberance of the 1920s and the undervaluation of the US stock market in the market trough of the 1930s. Irving Fisher, in his insightful 1932 book ‘Booms and Depressions’ (Fisher, 1932), cited pessimism as one of the main factors prolonging the slump. These ideas about the role of human psychology in the economy were given greater credence following the publication of the ‘General Theory of Employment, Interest and Money’ (Keynes, 1936). The role of expectations that Keynes’ new theory set out has been widely accepted. The role he attached to “animal spirits” (i.e. the role of human emotion in human cognition) has remained more controversial.[2]

The large boom and bust cycle of the period provides the ideal setting to test for the role of sentiment as it is often cited as being influenced heavily by some form of non-fundamental optimism or exuberance related to the US economy and the Stock Market (Galbraith, 1955). De Long and Shleifer (1991), find evidence of potential deviations from rational behaviour in the pricing of financial assets by examining closed-end fund premia. White (1990) and Rappaport and White (1993) suggest that an overvaluation of stocks of a

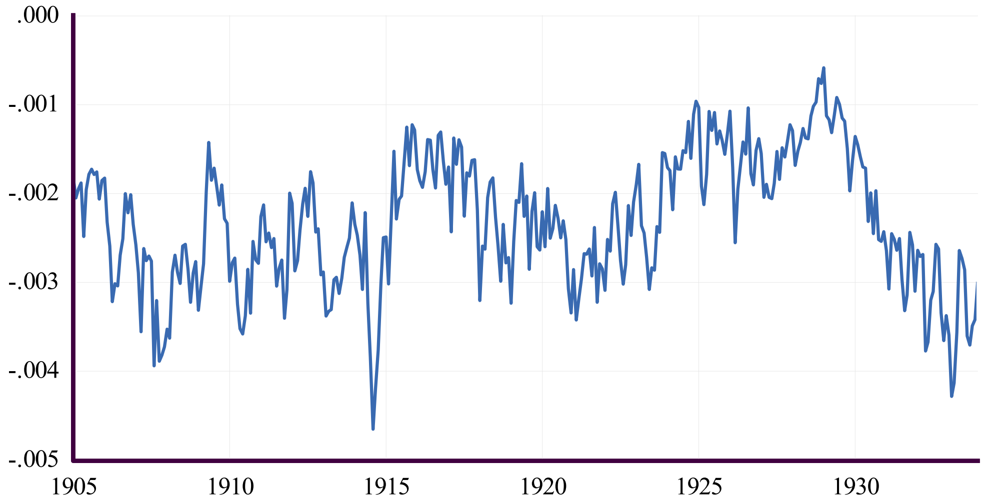
[1] The NBER measures ten recessions from 1899-1933.

[2] We interpret Keynes (1936) reference to “animal spirits” not as irrational changes in expectations of future economic conditions but rather “human psychology...states of mind...emotions unrelated to fundamentals”.

significant size occurred from 1927-9. Other studies find a potentially overvalued stock market for this period (Shiller 1981, 2001).[3]

We hypothesise that newspaper articles of the time contain information related to the state of emotions or confidence of economic agents as well as factual information about the actual fundamentals of the economy.[4] The emotion or sentiment component may have independent effects on the economy that are unrelated to the fundamentals that they describe.[5]

Figure 1: Index of Sentiment for the Wall Street Journal (1905 – 1934)



[3] Quantitative studies of the US stock market of the period point to non-fundamental factors as playing a significant role. Shiller (1981, 2000) uses a backward-looking dividend discount model to identify large over and under-pricing of the US Stock market in the 1920s and 30s, given the highly stable and growing collective dividend stream of US stocks.

[4] We are motivated by a number of new empirically backed theories developing in sociology, economics, anthropology, psychology and neuroscience, which suggest that narrative and emotion can be conceived to combine with cognitive and calculative skills to facilitate economic action (For example, Akerlof and Shiller, 2009; Bruner, 1990; Damasio, 1999; Lane and Maxfield, 2005; Mar and Oatley, 2008; Beckert, 2011, Barbelet, 2014; Pixley, 2009; Bandelj, 2009; Berezin, 2005, 2009; Tuckett, 2011).

[5] We suggest that fundamentals (i.e. data about economic fundamentals) are known via frames or narratives. Conviction Narrative Theory or CNT (Tuckett and Nikolic, 2017) posits that these frames are the way – as Keynes suggested (Keynes, 1936) – people get the ability – develop the optimistic/pessimstic expectations - to act. The emotional content of these frames may be unrelated to fundamentals but still exert an effect on them.

To investigate our hypothesis, we utilize a computer algorithm to conduct large-scale text analysis of digitized newspaper articles that measure the emotional word content in economic and financial narratives from over 2.4 million articles in The Wall St. Journal from 1889-1934. The database we produce from these articles contains over 925 million words in total and an average 1.7 million words per month. We use the RSS metric (Nyman et al., 2018) and adapt it to our new database of news articles. We apply our algorithm, which counts sentiment indicating or, 'emotionally laden' words to produce an index for The Wall St. Journal from 1889-1934. The results are illustrated in Figure 1 from 1905-1934.[6] Our sentiment index measures the balance between two emotion groups that are broadly analogous to excitement (approach) and anxiety (avoidance) in text data, using a dictionary of 150 words for each category utilizing ordinary English words[7] associated with these two major emotion groups. We calculate the difference between word counts from each word group normalized by the total word count to derive our sentiment index at a monthly frequency.

The index shown in Figure 1 highlights some notable points in US economic history and is consistent with accounts of these periods. For example, the 1907/8 trough around the time of the financial crisis, the sharp drop around the outbreak of the First World War in 1914 and a localized trough around the time of the sharp post-war recession of 1920-1. From 1921 to early 1929, the index shows a steady improvement, cresting at a 30-year peak in early 1929. From that zenith, a major slide through the end of the series in 1934, at the deepest point of the Great Depression and encompassing the Bank Holiday and revaluation of the Dollar, shows a sentiment level similar to that experienced at the outbreak of the First World War in 1914.

Having derived our index, we then carefully construct a database of the macro economy of the period from 1919-1934 in order to test the effect of sentiment on the economy. As Figure 1 highlights sentiment levels inclusive of the fundamentals which themselves impact sentiment, the identification requires that we isolate the effects of the sentiment index on the rest of the economy, independently of the fundamentals. To perform this empirical investigation, we build an eight variable vector error correction (VEC) model to recover the orthogonalized effects of our sentiment index on the real economy and financial markets. We then conduct historical decompositions for each series in the model for the counterfactual experiment where the "pure"

[6] We use data starting from 1905 as the data was more sparse in the early periods. The Wall St Journal consisted of only four pages of text in its first edition in 1889, which marks the start of the database.

[7] Using a British English lexicon

sentiment shock is set to 0. That is, counterfactual residuals are calculated from a set of counterfactual structural shocks with the "pure" sentiment shock set to 0 and all other structural shocks set to their estimated values. This counterfactual set of residuals are then fed back into the model yielding counterfactual series.

As we use relatively high frequency data we also produce detailed analysis of important subperiods during the boom and crash phases. We are able to show robust and economically meaningful independent effects on the real economy and how the timing and intensity of the effect changed for credit spreads, the money supply (M2), the S&P500 stock market index, industrial production, prices, interest rates and economic policy uncertainty (EPU) (Baker et al., 2016).

We are also able to investigate a further layer of how sentiment behaved, performing a historical decomposition for our sentiment index itself, with each of the identified orthogonal shocks removed. We therefore produce a counterfactual sentiment series under the case that one of the orthogonalized shocks from the variables in the system is set to 0 starting for a particular sub-period. We can thereby show which shocks to variables in the system are the ones that significantly contribute to the decrease or increase in the actual sentiment series, including a 'pure' sentiment shock.

We proceed as follows; Section 2 reviews the literature. Section 3 describes the WSJ article data and macroeconomic data, and the method for constructing the sentiment index. Section 4 sets out the vector error correction model, the variance decompositions and the results of the empirical investigation of the effect of sentiment on the real economy using counterfactual simulations. Section 5 sets out the discussion and Section 6 reports the conclusions.

2 Literature review

In both the finance and economics literature, research analysing text using a dictionary approach to search for words with positive and negative emotional content[8] has emerged (see for example, Tetlock 2007). Dominguez and Shapiro (2013) analyse newspaper and media sources to detect narrative shifts that could account for the slowness of the economic recovery. Soo (2013) quantifies the positive and negative tone of housing news in local newspaper articles about the US housing market, to isolate the roles of sentiment and fundamentals. Other research uses the analysis of news media or other digital sources to derive information about future expectations and behaviour (Ramey and Shapiro, 1999; Romer and Romer, 2010; Dominguez and Shapiro, 2013; Choi and Varian, 2012; Haddow et al., 2013)

Recent work focused specifically on the period in question have also borne fruit. Jalil and Rua (2016) use the historical narrative record from newspapers to determine whether inflation expectations shifted during the second quarter of 1933 as the recovery from the Great Depression took hold. Their results indicate that the shift in inflation expectations played a causal role in stimulating the recovery. Mathy and Ziebarth (2017) measure the effect of political uncertainty on economic outcomes using the case of Huey Long's tenure as governor and senator of Louisiana during the Great Depression. Based on primary sources they construct stock volatility indexes and newspaper mentions of terms related to "uncertainty" and the economy. Combined with employment data from the Census of Manufactures they suggest the effects of political uncertainty in Louisiana did not have a marked effect on the economy.

Manela and Moreira (2017) use the title and abstract of front-page news articles from The Wall St Journal from 1896 to 2009 and an algorithm trained on words associated with a modern indicator of stock market volatility (VIX) to reconstruct a News Implied Volatility or 'NVIX' time series back to 1896. They show that NVIX predicts future stock returns and conclude that NVIX captures time varying risk premia. Garcia (2013) measures the balance of positive and negative sentiment words in two daily financial news columns of The New York Times over the 20^{th} Century, finding generally small but heightened predictive effects on stock returns during recessions. Baker et al., (2016) focus on the macro economy and describe a

[8] The technical term in the Psychology literature is 'valence'

method to construct an 'Economic Policy Uncertainty' (EPU) index, based on analysing the frequency of the words related to government policy and 'uncertainty' in numerous digitized newspaper articles from several different sources. Using a VAR model, they show that their index of uncertainty has an independent effect on the macro-economy from 1920-84.

The extant literature described above has made headway towards explaining the influence of news-based sentiment and expectations data. We enhance the literature by investigating the impact of sentiment on several financial market and macroeconomic variables simultaneously and at high frequency for this period, thereby filling the gap on the boom and bust phases of the 1920s and 30s. We are the first study to our knowledge, to do this. Our innovative use of a very large volume of rich financial and economic news data over 1920-1934 enhances the reliability of our sentiment index. We are also able to innovate on the current literature for this period using historical decompositons to produce counterfactual simulations of the path of the economy. By showing how sentiment affected the trajectory of each of the individual subcomponents of the economy and how sentiment itself was influenced by orthogonal shocks to other components of economy we add to the current understanding of sentiment during business cycles.

3 Construction of Sentiment Index

3.1 Data

The analysis is based on the ProQuest digital archive of The Wall St. Journal (WSJ). The WSJ ProQuest archives consist of individual articles published between 1889 and 1934, which have been digitized and converted to an XML format that is machine-readable. This format allows them to be 'read' by a computer algorithm. In total we analyse 2.4 million articles to give a rich dataset of words for our algorithm to read. There is an average of 4,167 articles per month in the dataset. This equates to 925 million words over the whole sample or 1.7 million words per month.

3.2 Method

Following Nyman et al. (2018), we measure sentiment as a summary statistic of words in news articles related to the two emotion groups. For each of the two groups, we use a word list that consists of 150 words[9]. We use a 'bag of words' technique and tokenize the articles to be able to match the words in each word list with the words in each article.

For the summary statistic of a collection of texts T, we count the frequency of excitement words and anxiety words and then scale these numbers by the total number of words per period. To arrive at a single statistic, we subtract the anxiety statistic from the excitement statistic as in (1). Data are collected at daily frequency but collated at the monthly or quarterly level to ensure a higher signal to noise ratio.[10]

[9] **Approach/excitement** words include 'attract', 'encouraging', 'excels', 'excited', 'ideal', 'impress', 'impressively', 'incredible' and **Anxiety/avoidance** words include 'jitters', 'terrors' and 'worries', 'threatening', 'distrusted', 'panics', 'jeopardized' and 'eroding'.

[10] We use code written in 'Scala'- a Java programming language to perform the task.

$$RSS[T] = \frac{|Excitement| - |Anxiety|}{Size[T]} \tag{1}$$

Of the average 1.7 million words per month, there are an average of 14,216 emotion words, or less than 0.85 % that register any emotional content.[11]

As a robustness check of the WSJ data, we utilize the data available from the Federal Reserve Bank of St Louis - FRAZER[12] database, which contains digitized articles for the Commercial and Financial Chronicle - a popular weekly financial news source based in New York. The correlation between the CFC and WSJ from 1907-1934 is 0.74 indicating that we are using a sentiment index that captures consistent information on the economy and financial markets that is not specific to the WSJ.

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[11] One issue that may lessen the accuracy of our algorithm is that the modern lexicon we use may not match the historical lexicon. Although the fact that we use two counterbalancing indices which would net out any balancing effect on the index, we would still have a potential downward bias in the full effect if some key words were missed. Manela and Moreira (2017) illustrate that modern lexicons can successfully be used to measure 'news implied volatility- NVIX' back to 1889 although we are also limited in treating this potential downward bias.

[12] https://fraser.stlouisfed.org/title/commercial-financial-chronicle-1339?browse=1860s

4 Identification of the Impact of Sentiment on the Economy

In order to determine the impact of sentiment on the real economy a vector error correction model is estimated that contains the following variables: the (natural) logarithm of industrial production (IP), the logarithm of the Standard and Poors 500 stock market index (SP), the logarithm of the money supply (M2), the logarithm of the price level (CPI), the nominal interest rate (R) (the 3 month rate), the quality spread (QS), a measure of economic policy uncertainty (EPU), and our measure of sentiment (S). The variables are ordered as above so that we can determine the impact that sentiment has on the economy.

Our macro-economic data are; the Industrial production (IP)- Federal Reserve Bank of St. Louis - FRED Database[13], Standard and Poors' 500 stock market index (SP) (Shiller, 2017)[14], Money supply (M2) (Friedman and Schwarz, 1971), the consumer price index (CPI), the nominal interest rate (R) (the 3-month interest rate (Cecchetti, 1991), the quality spread (QS) (Bernanke, 1983) and a measure of economic policy uncertainty (EPU)[15] – (Baker et al., 2016). Time series for these data are depicted in Figure 2

An orthogonalized decomposition is used to identify orthogonal shocks as follows: the first shock is a shock to output (IP). The second identified shock is a shock to the stock market that is orthogonal to the shock to output. The third shock is a shock to the money supply that is orthogonal to both the output shock and the stock market shock. Next is a shock to the real interest rate shock that is orthogonal to the output, stock market, and money supply shocks. The first four variables of the system represent, in some respects, the real side of the economy. The next three variables deal with measures of uncertainty. These variables are the quality spread used by Bernanke (1983), economic policy uncertainty from Baker et al. (2016), and our measure of sentiment. The shock to the quality spread is orthogonal to the first four "real" shocks and the shock to economic policy uncertainty is orthogonal to the quality spread and the "real" shocks. This leaves us with the final shock, the shock to sentiment. This shock is orthogonal to all the previous seven shocks and is the residual shock. It is interpreted as the shock to sentiment controlling for shocks to output, the stock market, the money supply, the price level, the nominal interest rate, the quality spread, and economic policy uncertainty. In

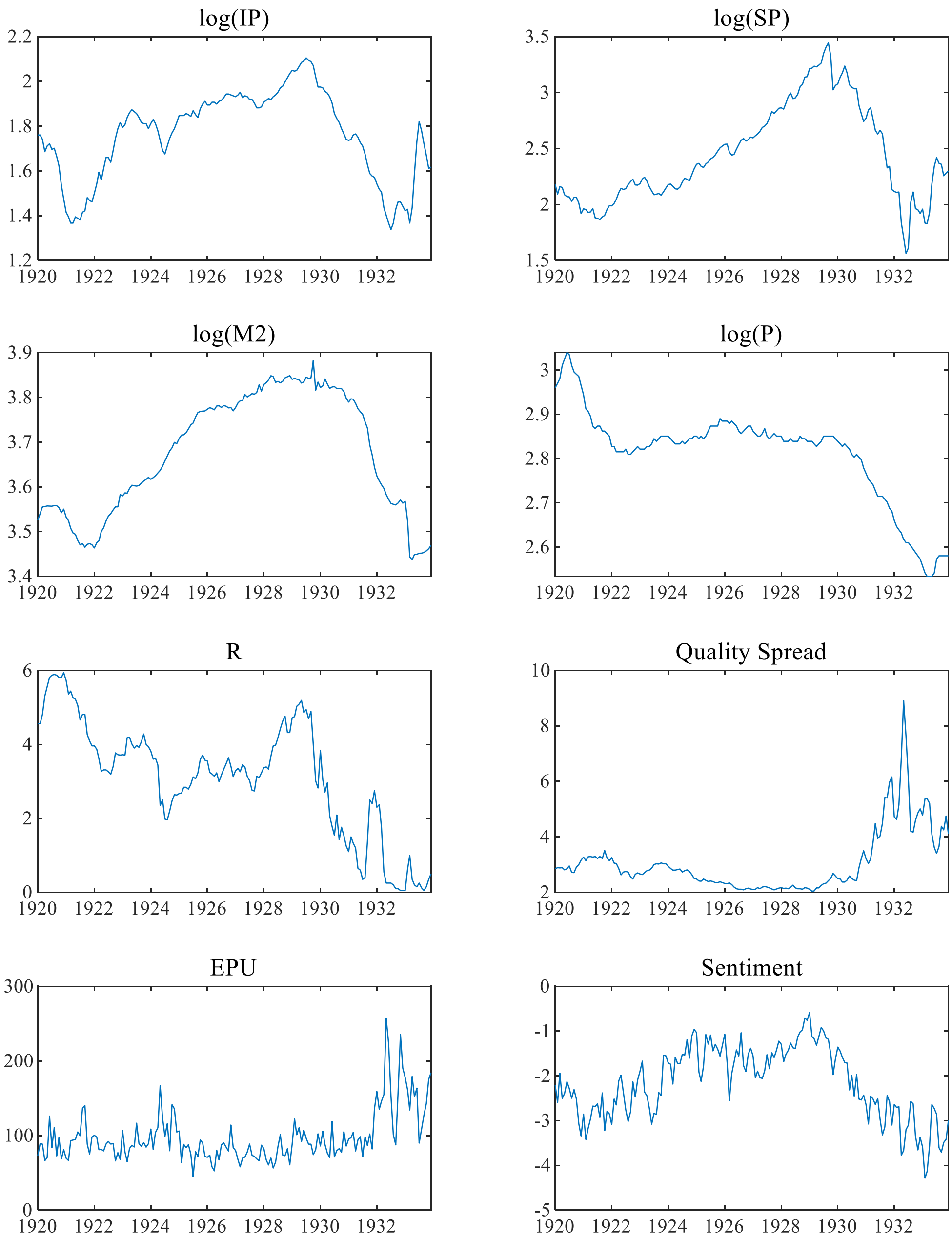
[13] https://fred.stlouisfed.org/series/INDPRO

[14] http://www.econ.yale.edu/~shiller/data.htm

[15] http://www.policyuncertainty.com

this sense we interpret the shock to sentiment as a “pure” sentiment shock that is orthogonal to the other shocks in the system. In this approach we make it as hard as possible for our sentiment variable to have an impact of the system.

Figure 2: Data Used in Analysis (1919 -- 1934)



In what follows we summarize the econometric tests we perform on the data to build the model that will be used to perform our analysis. We first test each series for the presence of a unit root. In Table 1 the unit root tests are reported using the standard augmented Dickey-Fuller (ADF) tests and the modified ADF tests of Rotemberg, Elliot, and Stock (1996) (ADF-GLS). The augmented test has better power than the standard ADF test when the data exhibits heteroscedasticity.

Table 1: Unit Root Tests for Full Sample (1919 – 1934)

Test	**Variable**	**Deterministic term**	**Test Statistic**	**Result**
ADF	Log IP	Trend + constant	-2.10	Unit Root
ADF-GLS	Log IP	Trend + constant	-2.14	Unit Root
ADF	Log S&P500	Trend + constant	-1.81	Unit Root
ADF-GLS	Log S&P500	Trend + constant	-1.75	Unit Root
ADF	Log M2	Trend + constant	-1.26	Unit Root
ADF-GLS	Log M2	Trend + constant	-0.625	Unit Root
ADF	Log CPI	Constant	-1.96	Unit Root
ADF-GLS	Log CPI	Constant	-1.63	Unit Root
ADF	Nominal interest rate	Trend + constant	-2.07	Unit Root
ADF-GLS	Nominal interest rate	Trend + constant	-1.98	Unit root
ADF	Quality Spread	Constant	-2.08	Unit Root
ADF-GLS	Quality Spread	Constant	-1.93	Unit Root
ADF	Ec. Pol. Unc.	Constant	-1.375	Unit Root
ADF-GLS	Ec. Pol. Unc.	Constant	-0.833	Unit Root
ADF	Sentiment	Constant	-0.905	Unit Root
ADF-GLS	Sentiment	Constant	-0.995	Unit Root

All time series contain unit roots and so we first check for cointegration using the Johansen cointegration test. A vector auto regression in levels was estimated and information criteria were calculated for lags of 1 through 8. The optimal number of lags in the level vector auto regression was found to be equal to 1 when using the Schwarz Bayesian information criterion (BIC) and equal to 2 when using Akaike's information criterion (AIC). The number of lags chosen by AIC was chosen in order to be conservative. This led to 1 lag of first differences being chosen for the Johansen cointegrating regression.

Table 2 contains the results of the cointegration test with one lag of the dependent variables included in each equation. There is evidence at the 5% level of two cointegrating relationships. Thus, we estimate a vector error correction model (VECM) with one lag and two cointegrating relationships.

Table 3 reports the information criteria (BIC and AIC) for a VEC model with 2 cointegrating relationships included. Both information criteria suggest that 1 lag of the first differences is appropriate to include in the VEC model. Thus, a VEC model with 2 cointegrating relationships and 1 lag is estimated.

Table 2: Cointegration Test Results: Rank Test

Hypothesized No. of Cointegrating relationships in H_0	Eigenvalue	Test Statistic	5% Critical Value	p-value
None *	0.348392	71.09993	52.36261	0.0002
At most 1 *	0.331155	66.76569	46.23142	0.0001
At most 2	0.202583	37.57865	40.07757	0.0931
At most 3	0.147017	26.39652	33.87687	0.2971
At most 4	0.089358	15.53843	27.58434	0.7046
At most 5	0.028997	4.884712	21.13162	0.9965
At most 6	0.024354	4.092872	14.26460	0.8494
At most 7	0.002018	0.335341	3.841465	0.5625

Table 3: Lag Length Determination for VEC model with 2 CI Relationships

Lags	BIC	AIC
1	-7.75*	-9.70*
2	-6.24	-9.40
3	-5.11	-9.49
4	-3.84	-9.46

4.1 Estimation of VEC Model for the period of March 1920 to December 1933

In this section, the VEC model is estimated for the sample period of June 1920 to December 1933. The time series that are included in the model are industrial production (*IP*), the stock market index (*SP*), money supply (*M2*), the price level (*P*), the three-month short-term nominal interest rate (*R*), the quality spread (*QS*), economic policy uncertainty (*EPU*), and our measure of sentiment (*S*). The time series are ordered as listed above so that the identified (orthogonalized) sentiment shock is interpreted as the "pure" sentiment shock after controlling for shocks to output, the stock market, money supply, price level, interest rate, the quality spread, and economic policy uncertainty. The interpretation of the sentiment shock is that it is the residual shock to sentiment that is not due to the previous "fundamental" shocks from the economy.

Both cointegration relationships include a constant to allow for trends in the level of the data and a non-zero constant in the cointegrating relationship. The estimated cointegrating relationships are

$$\begin{aligned}\log\left(IP_t\right) = 35.72 &- \underset{(0.83)}{4.38}\log\left(M2_t\right) - \underset{(1.34)}{4.66}\log\left(P_t\right) - \underset{(0.08)}{0.09}R_t \\ &- \underset{(0.11)}{0.31}QS_t - \underset{(0.00)}{0.02}EPU_t + \underset{(0.17)}{0.89}S_t + Z_{1t}\end{aligned} \tag{2}$$

and

$$\begin{aligned}\log\left(SP_t\right) = -418.60 &+ \underset{(17.68)}{74.63}\log\left(M2_t\right) + \underset{(17.40)}{30.55}\log\left(P_t\right) + \underset{(1.01)}{2.51}R_t \\ &+ \underset{(1.48)}{3.44}QS_t + \underset{(0.04)}{0.16}EPU_t - \underset{(2.16)}{12.34}S_t + Z_{2t}.\end{aligned} \tag{3}$$

The cointegrating relationships given in (2) and (3) are long-run equilibrium relationships. Sentiment enters into both relationships in a statistically significant way with sentiment having a positive impact on industrial production in the long run and a negative impact on the stock market index in the long run. Table 5 of the Appendix reports the estimation results for the VEC with one lag and two cointegrating vectors, Z_1 and Z_2. Orthogonalized shocks are identified by taking the Cholesky factor of the residual covariance matrix.

In order to determine the impact each identified shock has on the eight time series in the model we report the forecast error variance decomposition. These are reported in Figure 3 and Table 6 of the Appendix. The sentiment shock, whose impact is shown in magenta in Figure 3, is the shock to sentiment that is orthogonal to the shocks to output, the stock market, money supply, the price level, the nominal short-term interest rate, the quality spread, and economic policy uncertainty. This identified has little impact on output and the stock market over the full period. Sentiment does have an impact on the money supply and the price level. In particular, sentiment shocks accounts for up to 22% of the one-step ahead forecast error variance for money supply and up to 8% of the forecast error variance of the price level.

The forecast error variance decomposition, given in Figure 3, reports the average impact of a "pure" sentiment shock on each series in the model. The fact that the "pure" sentiment shock has little overall impact on industrial production and the stock market does not mean that the "pure" sentiment shock does not impact these series for some short periods of the sample. In order to see this, we construct historical decompositions. Figure 4 depicts the historical decompositions for each series in the model for the counterfactual experiment where the "pure" sentiment shock is set to 0. That is, counterfactual residuals are calculated from a set of counterfactual structural shocks with the "pure" sentiment shock set to 0 and all other structural shocks set to their estimated values. This counterfactual set of residuals are then fed back into the model yielding counterfactual series. In Figure 4, the actual series is depicted in blue while the counterfactual series is depicted in red. When the counterfactual series departs from the actual series the interpretation is that a "pure" sentiment shock influenced that series. Inspecting Figure 4, we see that there was a great diversion during the mid-1920s in money supply and price level from their counterfactual paths. We also observe that there is a diversion in industrial production during the mid-1920s as well, even though, on average, the forecast error variance decomposition suggests the "pure" sentiment shock has a very small impact on industrial production.

Figure 3: Forecast Error Variance Decompositions for the Period of March 1920 to December 1933.

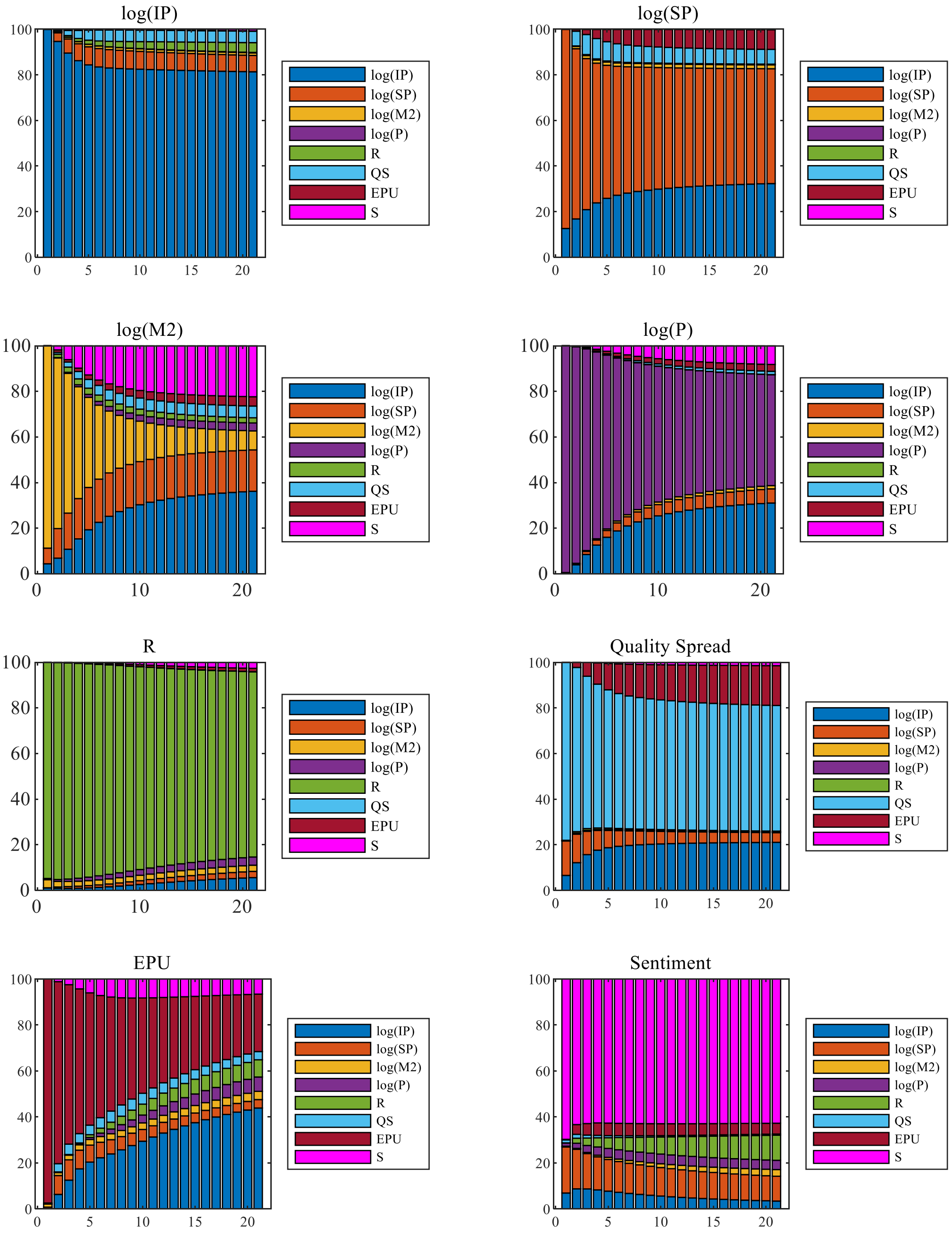
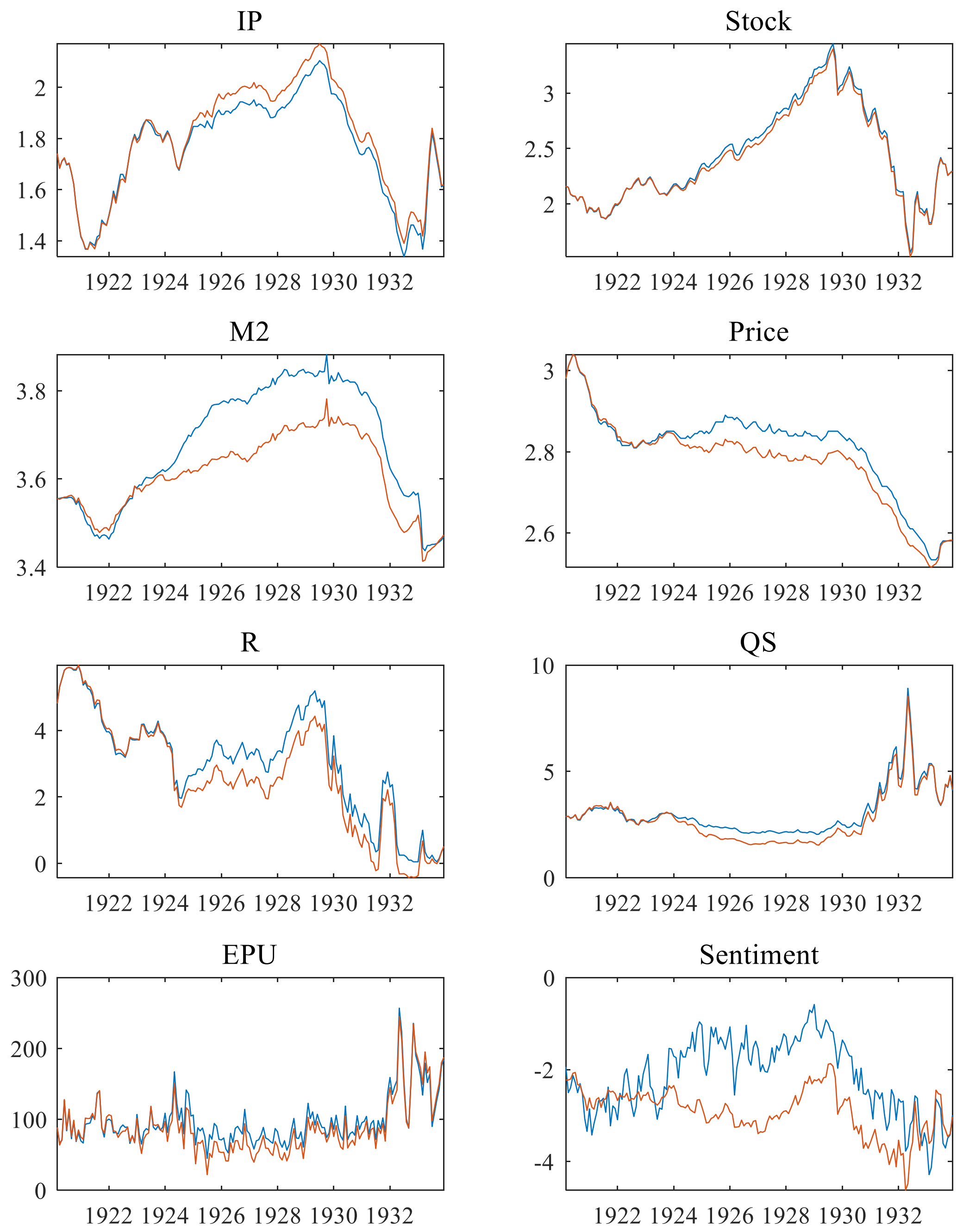


Figure 4: Historical Decomposition for All Series with Sentiment Shock Omitted (Full Sample: March 1920 to December 1933)



We next drill down into specific sub periods to investigate the impact that the "pure" sentiment shock has on the series in our model. Figure 5 depicts the historical decomposition of the series starting in June 1929. In this case, the counterfactual "pure" sentiment shock is set to 0 starting in July 1929. Prior to that, the counterfactual structural shock is identical to the actual structural shock. It is clear that sentiment is not playing a role in the first part of the period. This is best seen in the sentiment series. Prior to 1933, the sentiment series predicted by the rest of the shocks is similar to the actual sentiment series. At the end of the sample, there is a divergence in the actual sentiment series and the counterfactual series. It appears that sentiment played a role towards the end of the Depression, especially on prices and money supply. In fact, in the counterfactual economy (absent the "pure" sentiment shocks) the deflation in prices would not have been as great and the decline in money supply would also have been smaller. It appears that the "pure" sentiment shock towards the end of 1932 extended the decline of prices and money supply when fundamentals would have suggested an earlier recovery.

There does not appear to be any obvious "pure" sentiment shocks during the "Great Crash". Our interpretation of this is that during this period of great crisis, fundamentals are driving sentiment. Agents have a good idea as to the true state of the economy and so there is no room for the non-fundamental component of sentiment to have any effect.

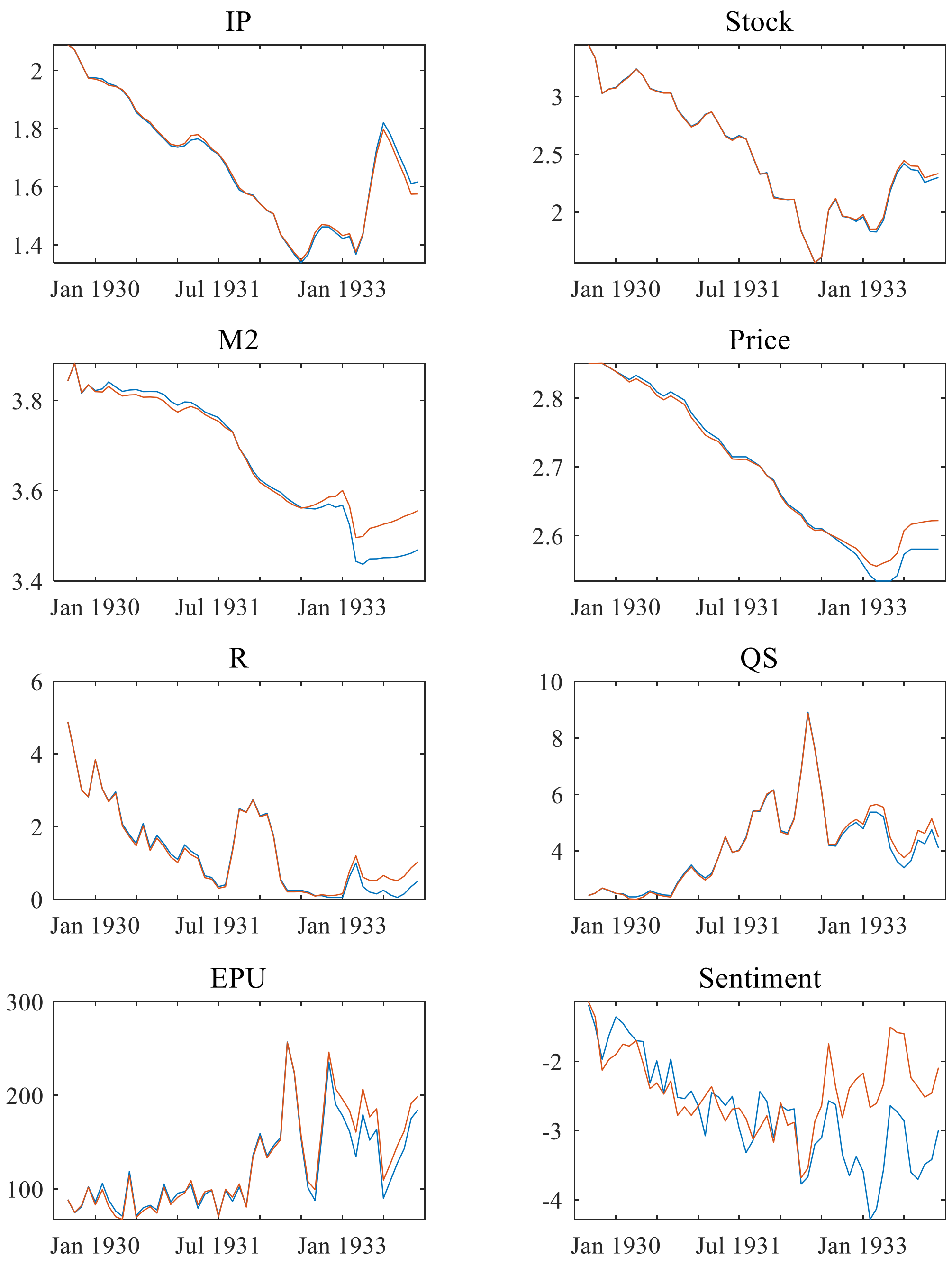
One consideration must be that the great uncertainty brought about by the "Great Crash" of 1929 is swamping the impact the sentiment shock for the full sample. In an orthogonalized VEC, if there were highly correlated shocks, or shocks with a substantial common component, we would expect the first shock to contain most of the information. In this case, we would expect the last shock, as ordered, would have little impact on variables with highly correlated shocks. After the "Great Crash" of 1929, we expect that there are some very big dominant "fundamental" shocks and that sentiment would be highly correlated to these dominant shocks. In this case, it is understandable to expect that agent's expectations are aligned with the "fundamental" shocks that are occurring. For the case of the aftermath of the "Great Crash" it is hard to expect that agents' sentiments would diverge from the reality given the nature of the Great Depression. However, we might expect to see divergence in agent's sentiment and "fundamentals" as the Great Depression was ending. While "fundamentals" might suggest the end of the recession, agents' sentiment might say otherwise. It appears from the historical decomposition depicted in Figure 5 that sentiment did diverge from "fundamentals" and this divergence in sentiment led to a longer and deeper deflation than what the "fundamentals" suggested.

The aftermath of the "Great Crash" was severe and so it might be the case that this period is driving the results reported so far. To check whether the estimated model is stable a "Chow-Test" is performed for a structural break in June 1929. A dummy variable is created that takes the value of 1 post June 1929 and the value of 0 otherwise. For each equation in the VEC model the break dummy is added as well as the break dummy interacted with each of the right-hand side variables of each equation. The Chow test then tests whether the coefficients of each of the added variables are jointly 0 using a Wald-type test. The result of the test overwhelmingly finds that there is a structural break in June of 1929. In the next section we estimate the model for the sub-sample prior to June 1929.

Table 4: Test for Structural Stability after June 1929

Null Hypothesis	Test Type	Test Statistic	p-value
No structural break	Wald (χ^2_{71})	331.67	0.00

Figure 5: Historical Decomposition of All Series with Sentiment Shock Omitted: Post June 1929



4.2 Summary of Results for the Period of May 1920 to June 1929.

The previous exercise is repeated for the subsample ending in June 1929. As before, a vector error correction model with 2 cointegrating relationships and 1 lag is estimated. The estimated cointegrating relationships are:

$$
\begin{aligned}
\log\left(IP_t\right) = 34.29 &- \underset{(1.20)}{3.58}\log\left(M2_t\right) - \underset{(1.23)}{5.73}\log\left(P_t\right) - \underset{(0.08)}{0.08}R_t \\
&- \underset{(0.33)}{0.87}QS_t - \underset{(0.003)}{0.004}EPU_t + \underset{(0.15)}{0.37}S_t + Z_{1t}
\end{aligned} \tag{4}
$$

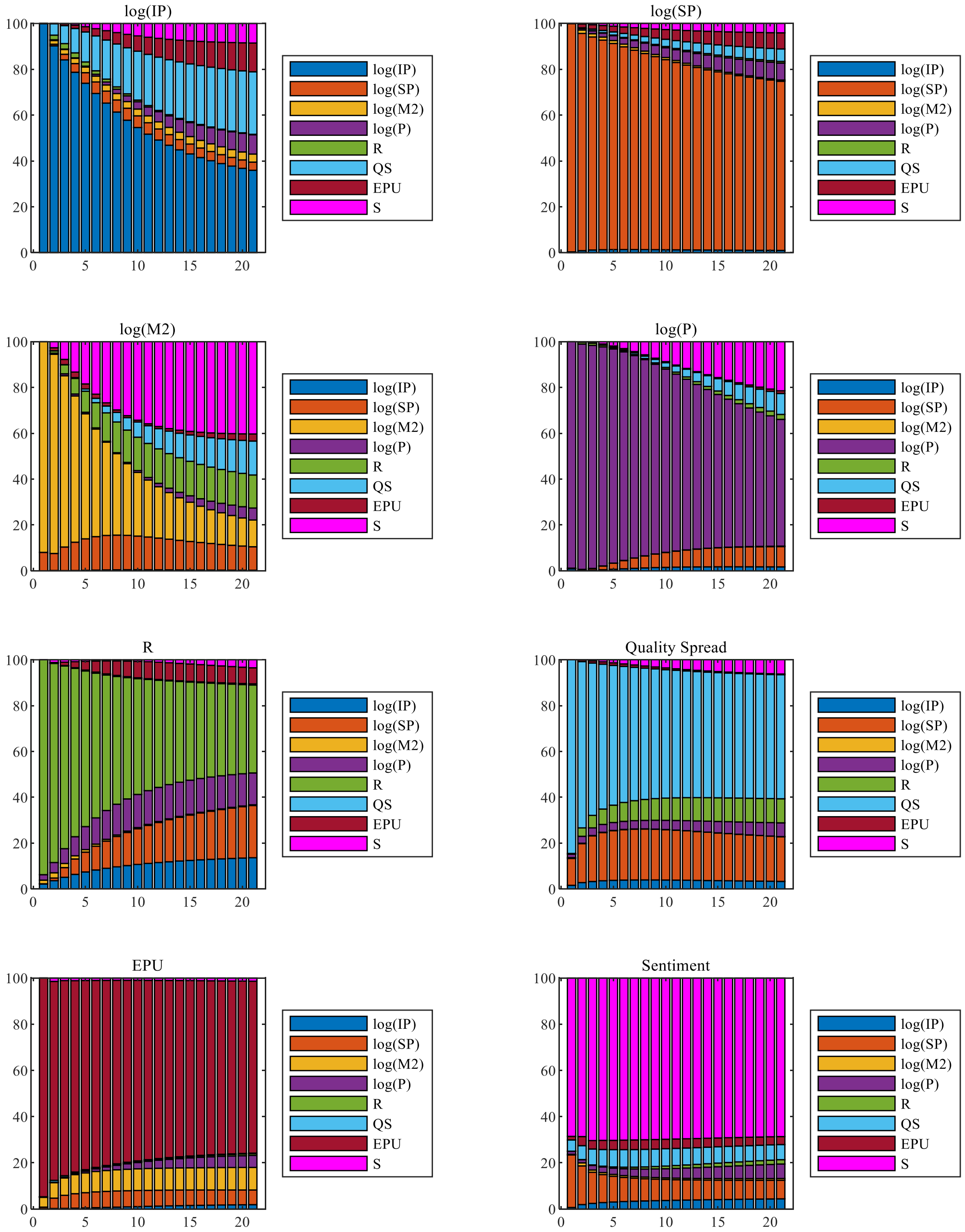
and

$$
\begin{aligned}
\log\left(SP_t\right) = -50.33 &+ \underset{(1.60)}{9.73}\log\left(M2_t\right) + \underset{(1.64)}{4.10}\log\left(P_t\right) + \underset{(0.10)}{0.47}R_t \\
&+ \underset{(0.43)}{0.76}QS_t + \underset{(0.004)}{0.001}EPU_t - \underset{(0.20)}{0.71}S_t + Z_{2t}.
\end{aligned} \tag{5}
$$

The results are similar for the early period but there are some significant changes in coefficients suggesting that the period after June, 1929 is different to the period prior to June 1929. This reinforces the result of the structural break test reported in Table 4. (The estimation results of the VEC test are shown in Table 6 of the Appendix.)

The forecast-error variance decomposition depicted in Figure 6 and reported in Table 8 (in the Appendix) show a different story to the variance decomposition for the full sample. In the sample that covers the 1920s only, the sentiment shock does appear to have some impact on output and the stock market. The sentiment shock continues to have a large impact on money supply and prices. The impulse response of industrial production (Figure 16 for the full sample and Figure 24 for the 1920s) show that for the full sample there is not a significant impact on industrial production using the estimates of the full sample, while using the estimates from the 1920s subsample there is a significant positive impact on industrial production.

Figure 6: Forecast Error Variance Decompositions for the Period of March 1920 to June 1929.

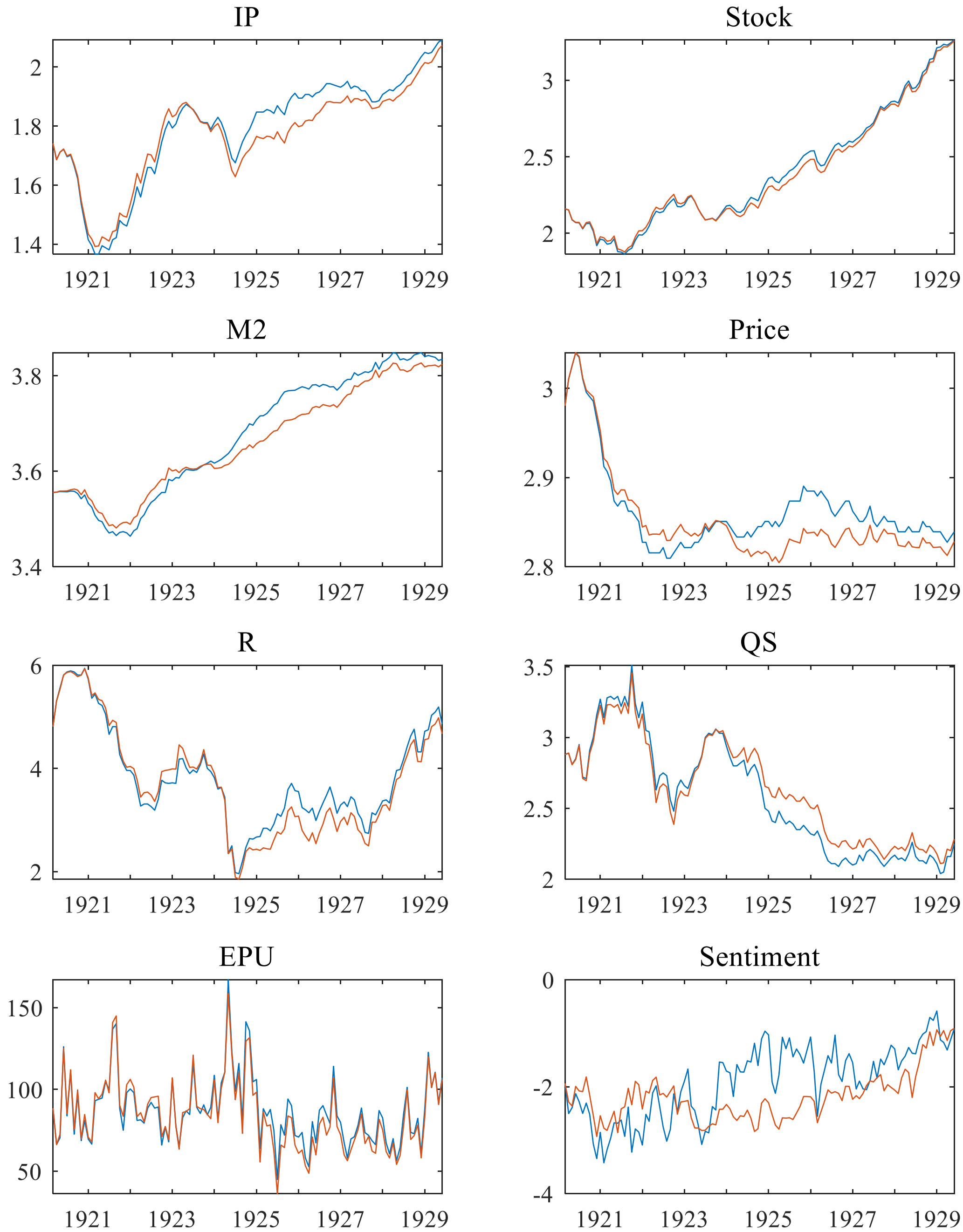


The variance decompositions report the overall impact of each shock on each variable. The next set of results aim to look at specific periods using historical decompositions. The historical decompositions look at what would happen with one of the structural shocks set to 0. That is, the set of identified structural shocks are altered by setting one shock to 0. The resulting "counterfactual" set of structural shocks are then fed back into the VEC model with the resulting "counterfactual" series compared to the actual series.

Figure 7 depicts the historical decomposition of the series in our model using the results from estimating our model using data up to June 1929. In Figure 7, the actual data is shown as the blue line and the red line depicts the counterfactual series for the case where there is no sentiment shock. When the red line is below the blue line the sentiment shock is interpreted as having a positive impact on the series. For example, for industrial production, after the middle of 1924 the counterfactual industrial production series is lower than the actual industrial production series, suggesting that sentiment raised industrial production above the level it would have been had there been no sentiment shock. This accords with the information contained in the sentiment series where we see that without the pure sentiment shock, sentiment would have been lower for the period after the middle of 1924. The red line in the sub-figure for sentiment is interpreted as the level of sentiment due to the other shocks.

Our results suggest that the "pure" sentiment component of the sentiment series does have an important impact on the real side of the economy during the 1920s. Note that the divergence between actual sentiment (the blue line) and sentiment predicted by "fundamentals" alone appears at the end of each recession. It is apparent that during recessions, there does not appear to be any divergence in sentiment from what is predicted from fundamentals but during recoveries the non-fundamental component of sentiment has an impact on the economy.

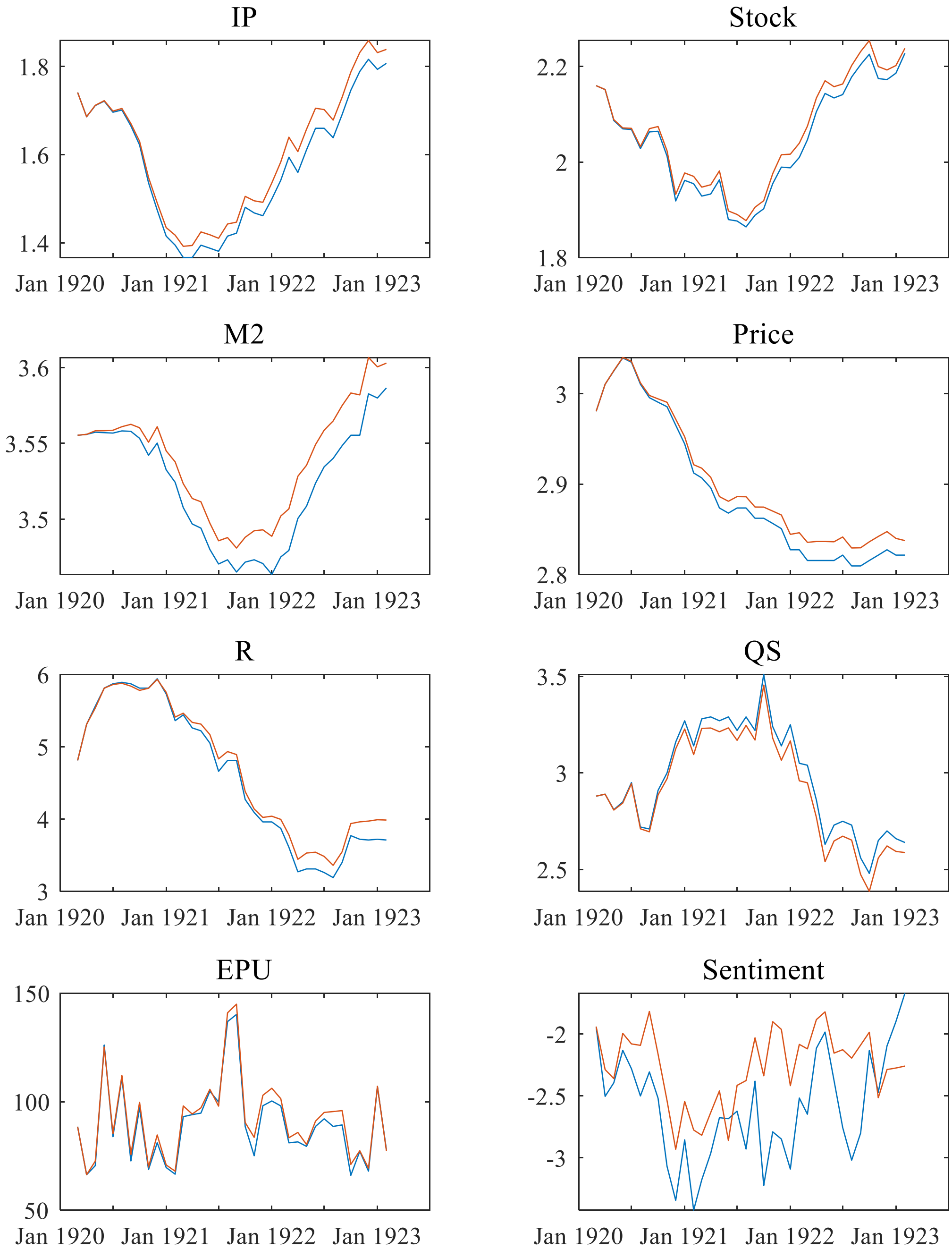
Figure 7: Historical Decomposition for All Series with Sentiment Shock Omitted (1920s Sample: March 1920 to June, 1929)



4.2.1 The Impact of Sentiment during the Early 1920s

Inspection of Figure 7 shows in the early 1920s actual sentiment was lower than what was predicted by fundamentals. Figure 8 depicts the period from 1920 to 1923. We can see the impact that the negative "pure" sentiment shock had on the economy. Industrial production was lower than that predicted by "fundamentals", as were stock prices, money supply and prices in general. The quality spread was higher, all suggesting that the negative "pure" sentiment shock had an adverse impact on the economy. The difference between the actual log industrial production and the counterfactual log industrial production series in March of 1921 is 0.0273 log points. This means that the impact of the "pure" sentiment shock was to lower industrial production by about 2.73% than what "fundamentals" predicted, suggesting that the impact of the "pure" sentiment shock was also economically significant. The other series where the "pure" sentiment shock had a sizeable impact was M2. In January, 1922 the difference between actual log(M2) and the counterfactual series was 3.4635 (actual) to 3.4887 (counterfactual). Without the "pure" sentiment shock money supply (M2) would have been 0.0252 log points higher or 2.52% higher than actual.

Figure 8: Historical Decomposition for All Series with Sentiment Shock Omitted 1920-1923 (1920s Sample: March 1920 to June, 1929)



4.2.2 The Impact of Sentiment in 1924

The next period where there was a divergence between actual sentiment and that predicted by “fundamentals” is the period encompassing the middle 1920s. This was a period where there were positive “pure” sentiment shocks. Figure 9 drills down to the middle 1920s starting in early 1924 and ending in early 1925. The historical decomposition shows that sentiment during 1924 was higher than what “fundamentals” would have predicted. This led to higher than predicted industrial production, higher value of stocks, higher money stock, higher prices, higher interest rates, and a lower quality spread. The difference between the actual industrial production series and the counterfactual industrial production series is of the order of 0.05 log points (5%), while the difference in the stock market is of the order of 0.03 log points (3%). Again, this is an economically significant difference. The effect of the accumulated positive “pure” sentiment shocks has a big impact on money supply and the price level with money supply being 2.96% higher at the end of 1924 than what the “fundamentals” would have suggested and prices being roughly 2% higher than what “fundamentals” would have suggested.

Figure 9: Historical Decomposition for All Series with Sentiment Shock Omitted Post 1924 (1920s Sample: March 1920 to June, 1929)

4.2.3 The Impact of Sentiment during 1926 and 1927

The period of 1926 to the end of 1927 was another interesting period with respect to sentiment. The actual sentiment series for this period is depicted in Figure 10. There is a very large drop in sentiment in March 1926. Using the estimated vector error correction model the identified "pure" sentiment shock is depicted in Figure 11. It is clear that there are significant negative "non-fundamental" shocks to sentiment in February and March of 1926, September 1926, and February 1927. There is clearly a major negative shock to sentiment in early 1926. The question is whether the observed downturn of measured sentiment in March, 1926 is solely caused by this downturn in "pure" sentiment.

Figure 10: Sentiment for 1926 and 1927

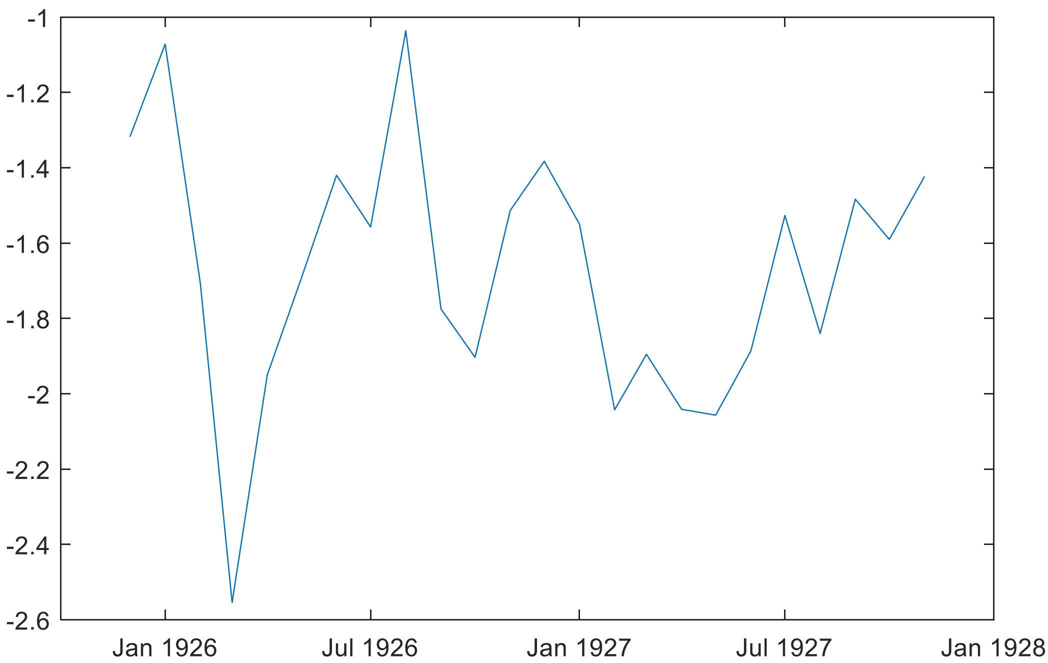


Figure 11: Pure Sentiment Shock for 1926 and 1927

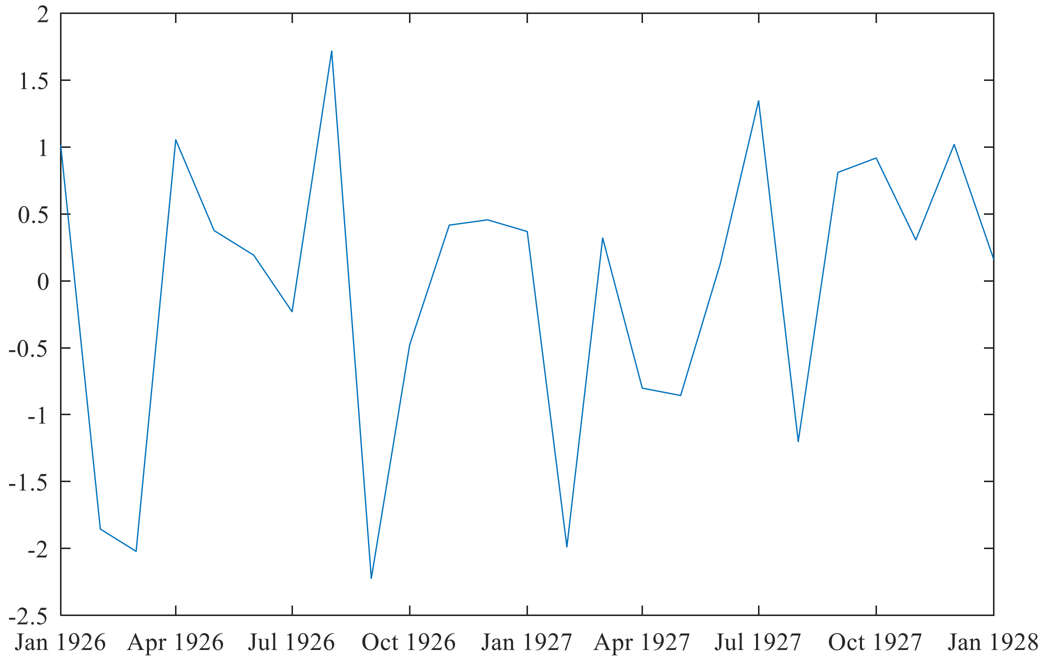
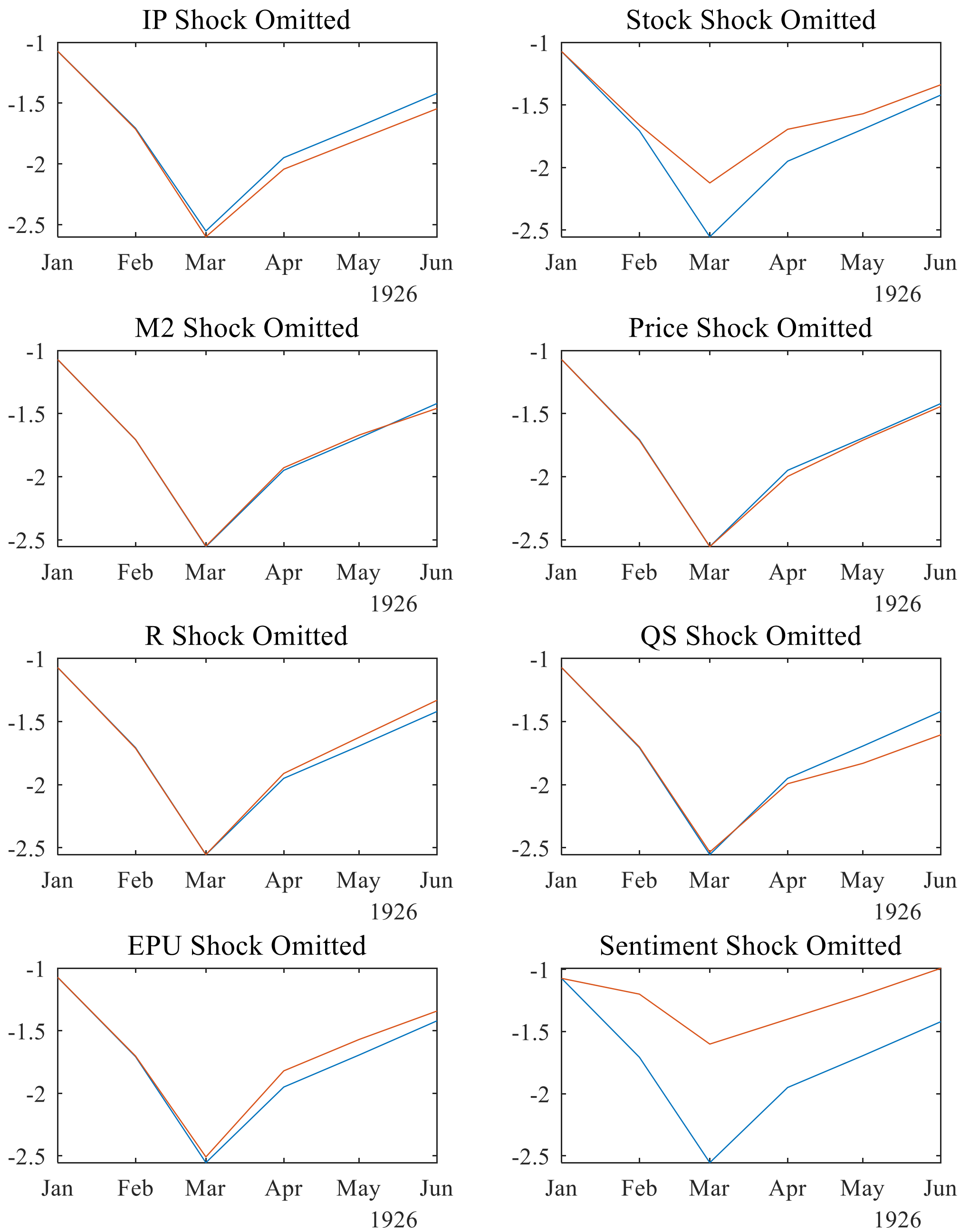


Figure 12 shows the historical decomposition for sentiment with each of the identified orthogonal shocks removed. Each subfigure shows the counterfactual sentiment series under the case that one of the orthogonalized shocks is set to 0 starting in January 1926. Figure 12 shows that the "stock market" shock and the "pure" sentiment shock are the only shocks that significantly contribute to the drop in sentiment in March, 1926.

In Figure 12 the shocks are set to 0 starting in February, 1926. Looking first at the subfigure that shows the counterfactual sentiment series with the "stock market" shock removed we see that the contribution of the "stock market" shock is around -0.4 points. That is, the difference between actual sentiment in March, 1926 (-2.55) and the counterfactual sentiment series with the "stock market" shock omitted (-2.12) is -0.43. The impact of the "pure" sentiment shock is much bigger. The value of the counterfactual sentiment series in March, 1926 with the "pure" sentiment shock omitted is -1.60 suggesting that the "pure" sentiment shock contributes -0.95 of the overall drop in sentiment. The overall drop in sentiment from January, 1926 to March, 1926 is -1.48 (from a value of -1.07 in January, 1926 to a value of -2.55 in March, 1926). Thus the "pure" sentiment shock contributes approximately 64% of the drop in sentiment from January, 1926 to March 1926 while the "stock market" shock contributes approximately 29% of the drop in sentiment for the same period.

Figure 12: Historical Decomposition for Sentiment: Early 1926



Next, we look at the impact the "pure" sentiment shock had on the time series in our model. This is done by calculating a counterfactual series for each series. The historical decomposition is constructed by setting the "pure" sentiment shock to 0 starting in February, 1926. The identification used is the triangular ordering, which means that, because sentiment is ordered last, it is imposed that the "pure" sentiment shock does not contemporaneously influence any of the other series in the model. The historical decomposition for each series of the model with the "pure" sentiment series set to 0 is depicted in Figure 13. Recall from Figure 11 that there were large negative shocks to "pure" sentiment in February and March of 1926. After that, the shocks to pure sentiment were small in magnitude and both positive and negative. It takes approximately two months for the full impact of the shocks in February and March to take effect. The impact on industrial production causes output to be lower than what the "fundamentals" (red line) would have predicted. By May 1926, industrial output is approximately 1 percentage point lower than predicted by fundamentals and by June 1926 industrial output is approximately 2 percentage points lower (the actual value of log industrial production in June 1926 is 1.911 while the predicted value is 1.929).

The overall impact of the negative "pure" sentiment shock in early 1926 is negative in that industrial production and the stock market are lower than what is predicted by fundamentals, money supply and prices are lower (again by about 1%) than predicted by fundamentals, while the short-term interest rate and quality spread are higher than what is predicted by fundamentals.

The second large negative "pure" sentiment shock occurs in September 1926. The impact of this negative shock is depicted in Figure 14. By January, 1927, the impact of "pure" sentiment shock on industrial production is approximately 1.5% and on the stock market is approximately 1%. The impact on money supply is around 1% while the impact on prices is approximately 0.5%.

Finally, there is a significant negative shock in February 1927. For most of the early part of 1927 the "pure" sentiment shock is negative. The accumulated impact on industrial production and the stock market is depicted in

Figure 15. The impact on industrial production and the stock market is approximately 2%. The impact of the "pure" sentiment shock on money supply is to lower money supply by about 1.8% and lower prices by about 1.6%.

Figure 13: Historical Decompositions with the "pure" sentiment shock omitted: Feb, 1926 – June, 1926

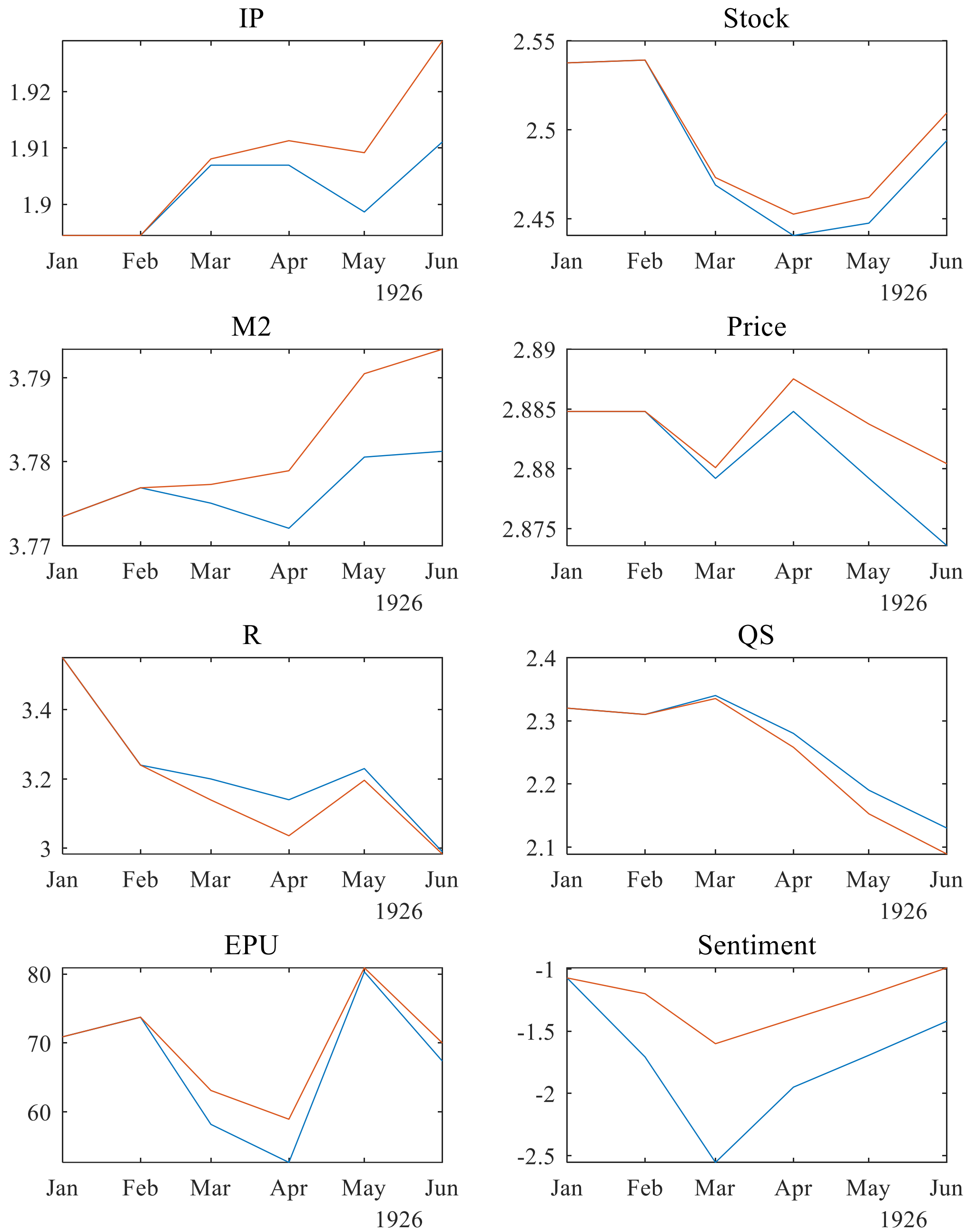


Figure 14: Historical Decompositions with the "pure" sentiment shock omitted: September, 1926 – January, 1927

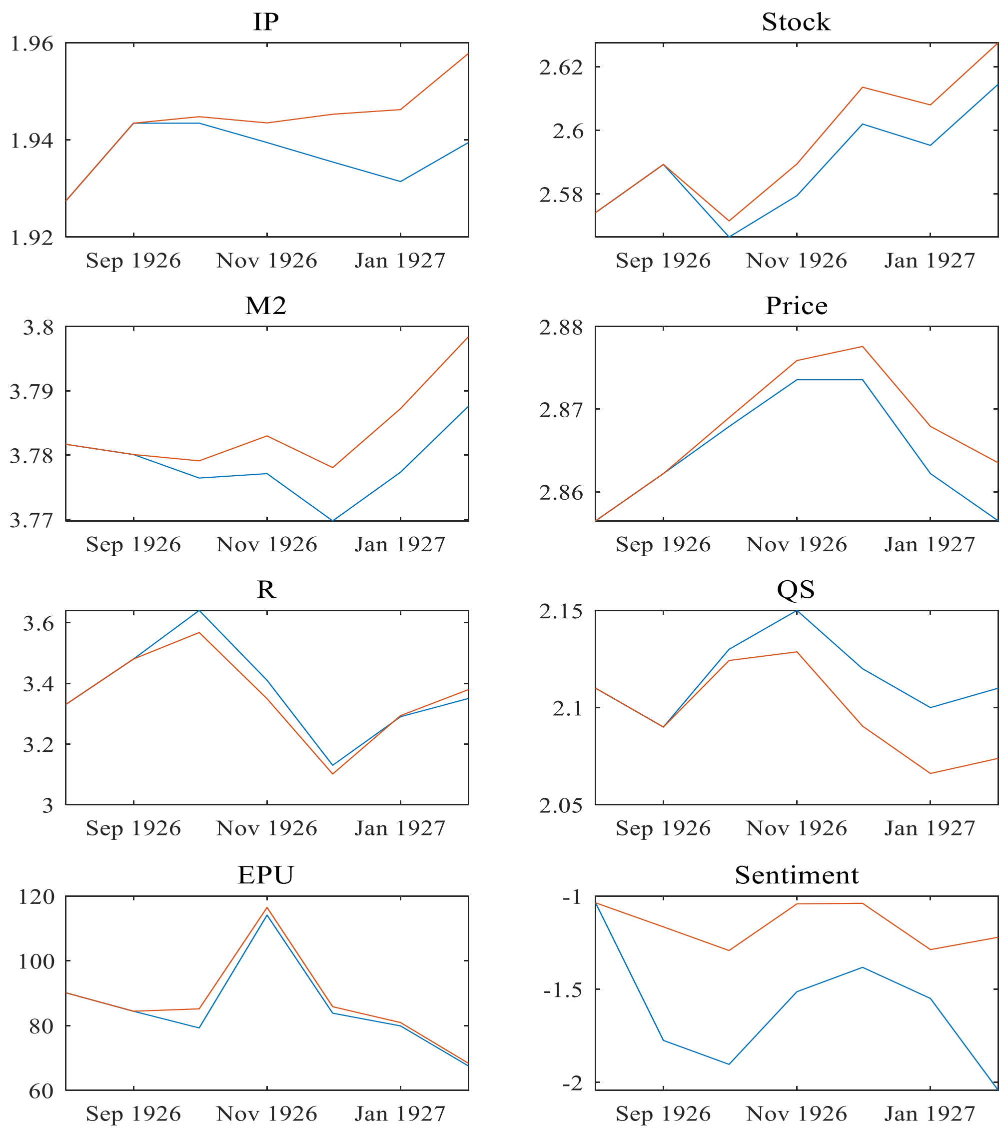
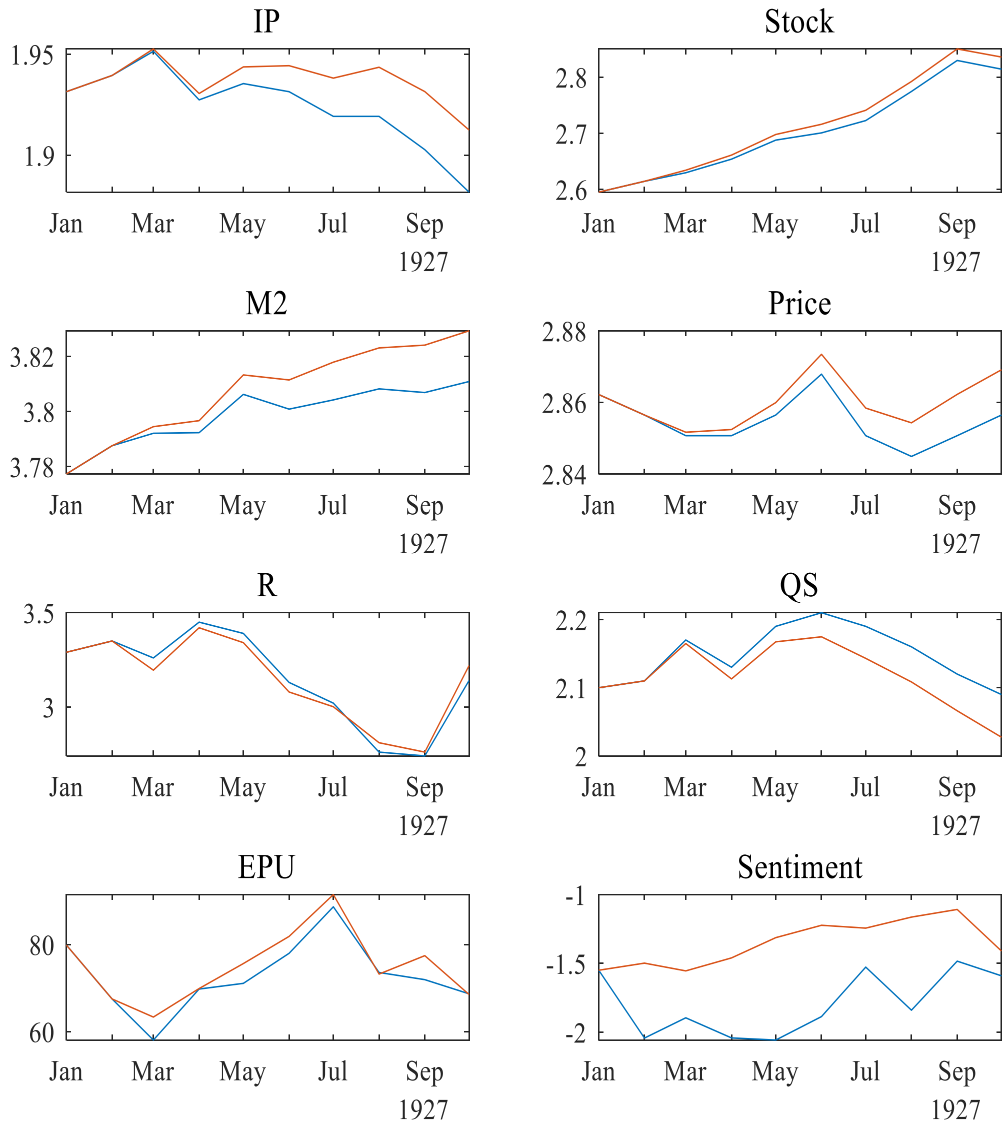


Figure 15: Historical Decompositions with the "pure" sentiment shock omitted: January, 1927 – October, 1927



5 Discussion

Taken together the results show strong evidence that orthogonalized shocks to sentiment contained in economic and financial news in The Wall St Journal had large effects on the real economy for the 1920-1929 period. Industrial production, Money supply (M2) and the price level all show high sensitivity to sentiment when the effects of the real economy have been discounted. We are able to show clearly that the effects flow from sentiment to the economy rather than vice versa. The size and timing of the effects are also economically meaningful and consistent with the idea that pure shocks to both positive and negative sentiments in the 1920s had material effects on the evolution of the real economy.

In 1924 sentiment appears to be boosting the economy with higher growth rates of output and money supply, and higher prices. After 1926 sentiment appears to be slowing the economy. These effects are consistent with the idea of 'animal spirits' (Keynes, 1936) but importantly, not corroborating the idea of an economy-wide monotonic increase in optimism leading to a peak in 1929, nor that the depression economy of 1929-34 was driven by pessimism. The results point to a much more nuanced impact of sentiment measured by our new sentiment index.

Our identification may be challenged on the grounds that rather than emotions, we are in fact capturing anticipations of TFP shocks (Barsky and Sims, 2011). Our careful selection of controls should account for these effects to a large extent. Another possible critique is that we could be identifying a dimension of the news which is 'fundamentals-based' but not yet reflected in the price of financial assets, such as in Calomiris and Mamysky (2018). These authors can predict financial asset returns, using sentiment in specific economic topic-related articles. We on the other hand, cannot consistently predict returns and therefore do not seem to capture such fundamentals.

The purpose of assessing sentiment is to think of an emotional input into financial and economic decisions, categorized in terms that alternately reveal basic levels of excitement (or euphoria) when risk is treated more lightly, and anxiety, when risk appears as something to be avoided. It is important from the point of view of this exercise to think of these emotions as independent of business conditions, so that there is not a simple feedback loop in which good outcomes encourage a greater risk tolerance.

The reader will wonder why at some dramatic moments in the course of business development there should be quite spectacular reassessments of risk: in the early 1920s actual sentiment was lower than a prediction generated from fundamentals. Dramatic negative turns in sentiment occurred in early 1921, again later in the year and in the summer of 1922. By contrast, 1924 was a year of positive sentiment shock. In 1926, two negative big shocks appeared, in March and in October. Finding an explanation for these extraneous shocks may be a matter of guess work: the point is that there were no obvious financial or economic linkages.

One suggestion might be that mood was being imported from other countries in a way that was more dramatic than the actual extent of economic interconnections. The US economy was fundamentally a closed economy in this period. At the end of the decade exports were only around 5 percent of GDP. Generations of economic historians have in consequence demonstrated that the downturn of 1929 and the stock market crash could not possibly have come from the Hawley Smoot tariff (for a summary, see Irwin 2011). On the other hand, the effect of US entry into the First World War, as well as the pandemic influenza of 1918-20 (which was widely named "Spanish influenza"), showed Americans a new sort of emotional or psychological connection with Europe. There was thus a phenomenon which psychologists term mirroring or modeling (and literary scholars think of as mimesis), when there is a social imitation of moods observed elsewhere.

The 1921 and 1922 episodes can be thought of in terms of a dramatic worsening of the prospects of European reconstruction: the downturn in the summer of 1922 reflects the aftermath of the assassination on June 24 of German Foreign Minister Walther Rathenau, which put paid to the chances of a reparation settlement. Some brief extracts will give the backdrop of the articles that were classed as producing negative sentiment (making their readers worried!). On February 2, 1921, one article talked about a coming "Red invasion of Germany." On February 4, a long article began "Investments in Germany should be avoided, says E.G. Horton [an investment banker] as German industrial efficiency is gone and taxation must be heavy." It went on to explain that "Today the hunger is worse than after the Thirty Years War." On June 26, 1922, after the Rathenau assassination, one article stated: "At opening of the foreign exchange, marks were quoted at a new low record. […] Present low value is thought here to result from the general idea that further inflation in Germany is unavoidable, which opinion is causing lame sales by speculators who have lost confidence in the mark. Dumping of exchange on the market by the Reichsbank [central bank] …. "In 1924, the benign input comes from the likely settlement of outstanding European issues, with the major reparations conference in London, which indeed had a successful outcome. After March 1926, the articles that push the sentiment index down are heavy with references to Belgium, where the franc was stabilized at too high a rate and the commentaries spoke of Belgium having "delivered herself into the hands of Anglo finance" (April 12, 1926), and "continued currency difficulties" in Belgium (April 24). Foreign psychology thus potentially helps to explain American sentiment swings.

This conjecture is of course not an attempt to give a definitive explanation of the sentiment phenomenon, but it represents a plausible causality. Future research could identify which countries lent themselves in particular to mirroring or modeling. A casual perusal suggests that Belgium and Germany had a particular salience, and that they appeared – clearly in different ways – as victims of the war and the peace treaty.

6 Conclusions

The 1920s and 30s are a reference period in US economic history when theories of "animal spirits" as partial but significant drivers of the economy, distinct from fundamentals, were given greater credence following the 1936 publication of the General Theory of Employment, Interest and Money (Keynes, 1936). The role of expectations this new theory set out has been widely accepted. The role he attached to "animal spirits" (i.e. the role of emotion in cognition) has remained more controversial.

We interpret Keynes (1936) reference to "animal spirits" not as irrational changes in expectations of future economic conditions but rather "human psychology...states of mind...emotions unrelated to fundamentals". We hypothesise that newspaper articles of the time contain information related to the state of emotions or confidence of economic agents as well as factual information about the actual fundamentals of the economy. We utilize a new dataset of the WSJ from 1889-1934, which contains rich text data in 2.4 million news articles and measure their sentiment or, emotional content, using algorithmic text searches to derive a new index for the period. We use vector error correction models to identify the shocks to sentiment that are orthogonal to shocks to industrial production, S&P500 stock index, M2, interest rates, prices, credit spreads and economic policy uncertainty for 1920-1934. We then construct historical decompositions for each series in the model for the counterfactual experiment where the "pure" sentiment shock is set to 0. That is, counterfactual residuals are calculated from a set of counterfactual structural shocks with the "pure" sentiment shock set to 0 and all other structural shocks set to their estimated values. This counterfactual set of residuals are then fed back into the model yielding counterfactual series. We examine the behaviour of the actual and simulated path of components of the economy to reveal the timing and intensity of the effect.

The high frequency of our analysis and our counterfactual simulations allow for some clear and valuable inferences. Sentiment did play a statistically significant and economically large role during the 1920s in both accelerating and dampening the path of the economy, and with a highly variable intensity. The effects of sentiment on industrial production, M2 and the S&P500 are large, having an impact of up to 5 % for industrial production, 3% for M2 and 3% for the S&P500, for specific time-periods.

We therefore encourage further analysis of such effects and the refinement of the techniques used to isolate these effects.

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Appendix

Table 5: Estimation Results for VEC for period March 1920 – December 1933

	$\Delta\log(IP_t)$	$\Delta\log(SP_t)$	$\Delta\log(M2_t)$	$\Delta\log(P_t)$	ΔR_t	ΔQS_t	ΔEPU_t	ΔS_t
Z_{1t-1}	-0.027	0.098	0.026	0.013	0.136	-0.796	-72.316	0.012
	(0.016)	(0.039)	(0.007)	(0.005)	(0.210)	(0.221)	(13.082)	(0.229)
Z_{2t-1}	-0.002	0.008	0.003	0.001	0.010	-0.048	-4.250	-0.011
	(0.001)	(0.003)	(0.001)	(0.000)	(0.016)	(0.017)	(1.021)	(0.018)
$\Delta\log(IP_{t-1})$	0.407	0.199	-0.014	0.050	-0.704	-2.050	-73.720	0.803
	(0.071)	(0.174)	(0.031)	(0.021)	(0.928)	(0.973)	(57.738)	(1.009)
$\Delta\log(SP_{t-1})$	0.123	0.078	0.016	0.005	0.407	0.117	-94.367	-0.286
	(0.039)	(0.095)	(0.017)	(0.012)	(0.509)	(0.534)	(31.690)	(0.554)
$\Delta\log(M2_{t-1})$	-0.302	-0.918	-0.152	0.015	2.319	2.710	14.260	0.209
	(0.184)	(0.450)	(0.079)	(0.055)	(2.406)	(2.523)	(149.654)	(2.615)
$\Delta\log(P_{t-1})$	0.139	-0.543	0.031	0.232	1.080	3.562	277.352	2.358
	(0.268)	(0.655)	(0.115)	(0.080)	(3.501)	(3.671)	(217.794)	(3.805)
ΔR_{t-1}	0.003	0.021	-0.002	0.004	0.144	-0.129	-6.175	0.172
	(0.006)	(0.015)	(0.003)	(0.002)	(0.081)	(0.085)	(5.068)	(0.089)
ΔQS_{t-1}	-0.009	-0.094	-0.003	0.000	0.027	0.368	22.013	-0.107
	(0.006)	(0.016)	(0.003)	(0.002)	(0.084)	(0.088)	(5.204)	(0.091)
ΔEPU_{t-1}	0.000	0.000	0.000	0.000	0.000	0.001	-0.112	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.075)	(0.001)
ΔS_{t-1}	0.008	0.003	-0.003	-0.001	-0.012	-0.131	-3.075	-0.097
	(0.006)	(0.014)	(0.003)	(0.002)	(0.076)	(0.080)	(4.754)	(0.083)
C	0.000	0.001	-0.001	-0.002	-0.019	0.006	0.841	0.008
	(0.002)	(0.005)	(0.001)	(0.001)	(0.027)	(0.028)	(1.664)	(0.029)
R^2	0.46	0.33	0.35	0.34	0.04	0.25	0.41	0.15
$\bar{R}^2$	0.42	0.29	0.31	0.29	-0.02	0.20	0.37	0.09
Log like.	381.19	233.10	521.76	582.25	-45.12	-52.99	-730.76	-58.92
Akaike AIC	-4.46	-2.68	-6.15	-6.88	0.68	0.77	8.94	0.84
Schwarz SC	-4.25	-2.47	-5.95	-6.68	0.88	0.98	9.14	1.05
Log likelihood	909.169							
AIC	-9.700832							
BIC	-7.751153							

Table 6: Forecast Error Variance Decomposition for VEC model estimated using data from March 1920 to December 1933.

Variance Decomposition of Industrial Production

Orthogonalized Shocks:

Period	IP	Stocks	M2	Prices	R	QS	EPU	S
1	100.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	94.633	3.753	0.397	0.038	0.144	0.619	0.030	0.387
3	89.538	6.157	0.791	0.026	0.701	2.289	0.017	0.481
4	86.186	7.424	0.993	0.016	1.302	3.624	0.028	0.428
5	84.358	7.942	1.100	0.014	1.783	4.401	0.067	0.336
10	82.446	7.827	1.187	0.048	3.051	5.037	0.165	0.238
15	81.851	7.473	1.150	0.129	3.748	5.041	0.134	0.474
20	81.405	7.211	1.112	0.207	4.211	5.016	0.108	0.730

Variance Decomposition of Stock Prices

Orthogonalized Shocks:

Period	IP	Stocks	M2	Prices	R	QS	EPU	S
1	12.608	87.392	0.000	0.000	0.000	0.000	0.000	0.000
2	16.790	74.649	0.972	0.068	0.200	6.461	0.784	0.075
3	20.870	66.266	1.291	0.069	0.379	8.815	2.169	0.141
4	23.839	61.276	1.408	0.048	0.411	8.913	3.979	0.126
5	25.828	58.340	1.475	0.045	0.381	8.452	5.370	0.109
10	29.870	53.324	1.600	0.104	0.250	7.041	7.687	0.123
15	31.384	51.471	1.656	0.138	0.204	6.674	8.295	0.178
20	32.188	50.483	1.686	0.161	0.179	6.497	8.587	0.220

Variance Decomposition of Money Supply (M2)

Orthogonalized Shocks:

Period	IP	Stocks	M2	Prices	R	QS	EPU	S
1	4.402	6.858	88.740	0.000	0.000	0.000	0.000	0.000
2	6.881	12.948	74.826	0.162	1.478	0.823	1.071	1.809
3	10.781	15.835	61.268	0.488	2.285	2.211	1.076	6.055
4	15.319	17.674	49.050	0.872	2.589	3.208	1.493	9.795

5	19.315	18.549	39.545	1.281	2.726	3.857	1.945	12.782
10	30.290	18.893	17.770	2.654	2.613	4.866	3.317	19.598
15	34.194	18.473	11.343	3.196	2.406	5.067	3.827	21.494
20	35.942	18.195	8.687	3.447	2.288	5.132	4.063	22.246

	Variance Decomposition of Prices (CPI)							
	Orthogonalized Shocks							
Period	IP	Stocks	M2	Prices	R	QS	EPU	S
1	0.358	0.078	0.110	99.454	0.000	0.000	0.000	0.000
2	3.978	0.429	0.203	94.958	0.268	0.003	0.065	0.096
3	8.485	1.344	0.362	88.426	0.277	0.064	0.378	0.664
4	12.591	2.223	0.548	81.925	0.235	0.218	0.751	1.508
5	16.027	2.952	0.706	76.219	0.191	0.390	1.113	2.401
10	25.401	4.943	1.144	59.555	0.073	0.977	2.265	5.643
15	29.037	5.757	1.318	52.609	0.039	1.265	2.741	7.234
20	30.794	6.159	1.403	49.158	0.026	1.417	2.977	8.066

	Variance Decomposition of Nominal Interest Rate (3 month)							
	Orthogonalized Shocks							
Period	IP	Stocks	M2	Prices	R	QS	EPU	S
1	1.017	0.119	3.551	0.548	94.766	0.000	0.000	0.000
2	0.919	0.574	2.459	0.824	95.086	0.058	0.075	0.004
3	0.877	0.775	2.258	1.067	94.772	0.061	0.183	0.007
4	0.942	0.885	2.196	1.302	94.278	0.064	0.283	0.050
5	1.093	0.986	2.185	1.537	93.596	0.068	0.396	0.137
10	2.589	1.659	2.373	2.527	88.939	0.046	0.850	1.017
15	4.217	2.273	2.569	3.142	84.674	0.036	1.192	1.897
20	5.398	2.686	2.699	3.523	81.718	0.039	1.422	2.515

	Variance Decomposition of Quality Spread							
	Orthogonalized Shocks							
Period	IP	Stocks	M2	Prices	R	QS	EPU	S
1	6.561	15.111	0.021	0.089	0.190	78.028	0.000	0.000
2	12.144	12.520	0.264	0.174	0.659	72.019	2.217	0.003

3	15.680	10.242	0.314	0.124	0.754	66.799	6.013	0.074
4	17.644	8.632	0.315	0.096	0.692	63.083	9.276	0.262
5	18.722	7.574	0.300	0.102	0.614	60.669	11.539	0.480
10	20.373	5.494	0.250	0.122	0.430	56.876	15.410	1.045
15	20.835	4.734	0.230	0.116	0.373	55.734	16.699	1.279
20	21.035	4.326	0.218	0.112	0.343	55.168	17.379	1.420

Variance Decomposition of Economic Policy Uncertainty

Orthogonalized Shocks

Period	IP	Stocks	M2	Prices	R	QS	EPU	S
1	0.015	0.737	1.314	0.023	0.016	0.437	97.458	0.000
2	6.288	8.212	1.267	0.141	0.153	3.588	79.196	1.155
3	12.479	8.846	2.027	0.123	0.157	4.530	69.345	2.493
4	17.395	8.137	2.323	0.344	0.472	4.069	62.933	4.327
5	20.335	7.381	2.443	0.867	1.220	4.172	57.536	6.045
10	29.414	5.120	2.852	3.410	4.742	4.724	41.463	8.275
15	37.485	4.193	3.261	5.027	6.420	4.140	31.917	7.558
20	42.991	3.735	3.532	6.083	7.349	3.669	25.901	6.740

Variance Decomposition of Sentiment

Orthogonalized Shocks

Period	IP	Stocks	M2	Prices	R	QS	EPU	S
1	6.889	20.024	0.319	1.421	0.042	1.284	0.274	69.748
2	8.701	17.202	0.402	2.220	2.197	1.683	4.261	63.335
3	8.662	15.348	0.527	3.040	3.217	1.294	5.011	62.900
4	8.241	14.376	0.723	3.573	4.002	1.059	5.399	62.627
5	7.703	13.791	0.893	3.885	4.671	0.911	5.447	62.700
10	5.564	12.405	1.658	4.194	7.439	0.587	5.193	62.959
15	4.294	11.520	2.313	4.140	9.348	0.510	4.952	62.924
20	3.510	10.888	2.823	4.047	10.714	0.495	4.746	62.778

Table 7: Estimation Results for VEC for period March 1920 – June 1929

	$\Delta\log(IP_t)$	$\Delta\log(SP_t)$	$\Delta\log(M2_t)$	$\Delta\log(P_t)$	ΔR_t	ΔQS_t	ΔEPU_t	ΔS_t
Z_{1t-1}	-0.05	-0.03	0.02	0.01	0.55	-0.17	27.80	-0.25
	(0.02)	(0.03)	(0.01)	(0.01)	(0.18)	(0.07)	(16.71)	(0.30)
Z_{2t-1}	-0.01	-0.02	0.02	0.01	0.30	-0.11	17.16	-0.24
	(0.01)	(0.02)	(0.00)	(0.00)	(0.12)	(0.05)	(10.85)	(0.19)
$\Delta\log(IP_{t-1})$	0.23	0.12	-0.02	0.03	0.48	-0.25	22.73	2.04
	(0.09)	(0.13)	(0.03)	(0.03)	(0.91)	(0.35)	(82.86)	(1.49)
$\Delta\log(SP_{t-1})$	0.04	0.14	-0.04	-0.01	1.63	-0.32	-181.74	-2.15
	(0.07)	(0.11)	(0.02)	(0.03)	(0.73)	(0.28)	(66.43)	(1.19)
$\Delta\log(M2_{t-1})$	-0.48	1.17	-0.21	0.11	-0.98	-0.06	-365.04	6.13
	(0.29)	(0.45)	(0.09)	(0.12)	(3.11)	(1.21)	(283.05)	(5.09)
$\Delta\log(P_{t-1})$	0.46	-0.39	0.02	0.21	1.71	1.36	-68.07	1.11
	(0.26)	(0.40)	(0.08)	(0.10)	(2.73)	(1.06)	(249.08)	(4.47)
ΔR_{t-1}	0.02	-0.01	0.00	0.01	0.12	0.05	6.54	-0.06
	(0.01)	(0.01)	(0.00)	(0.00)	(0.10)	(0.04)	(8.92)	(0.16)
ΔQS_{t-1}	-0.07	-0.01	0.01	0.00	-0.29	-0.14	-26.97	-0.17
	(0.03)	(0.04)	(0.01)	(0.01)	(0.27)	(0.11)	(24.70)	(0.44)
ΔEPU_{t-1}	0.00	0.00	0.00	0.00	0.00	0.00	-0.39	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.10)	(0.00)
ΔS_{t-1}	-0.01	0.01	0.00	0.00	-0.13	0.01	7.56	-0.13
	(0.01)	(0.01)	(0.00)	(0.00)	(0.06)	(0.02)	(5.68)	(0.10)
C	0.00	0.00	0.00	0.00	-0.01	0.00	2.53	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.01)	(2.12)	(0.04)
R^2	0.46	0.19	0.44	0.26	0.21	0.14	0.25	0.15
$\bar{R}^2$	0.40	0.11	0.38	0.19	0.13	0.05	0.18	0.06
Log like.	284.90	236.76	419.20	386.32	20.15	125.75	-485.19	-35.03
Akaike AIC	-4.89	-4.03	-7.29	-6.70	-0.16	-2.05	8.86	0.82
Schwarz SC	-4.62	-3.76	-7.02	-6.44	0.10	-1.78	9.13	1.09
Log likelihood		995.58						
AIC		-15.92						
BIC		-13.40						

Table 8: Forecast Error Variance Decomposition for VEC model estimated using data from March 1920 to June 1929.

Variance Decomposition of Industrial Production

Orthogonalized Shocks:

Period	IP	Stocks	M2	Prices	R	QS	EPU	S
1	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	90.25	0.71	1.63	0.30	2.03	4.97	0.08	0.03
3	84.11	2.46	2.10	0.18	2.37	7.88	0.74	0.17
4	78.71	3.81	2.30	0.18	2.19	10.66	1.46	0.69
5	73.93	4.61	2.45	0.39	1.85	13.07	2.30	1.41
10	54.59	5.12	2.96	3.18	0.73	21.33	6.68	5.40
15	43.08	4.32	3.28	6.10	0.39	25.21	10.07	7.56
20	36.79	3.67	3.49	8.10	0.25	27.05	12.23	8.43

Variance Decomposition of Stock Prices

Orthogonalized Shocks:

Period	IP	Stocks	M2	Prices	R	QS	EPU	S
1	0.35	99.65	0.00	0.00	0.00	0.00	0.00	0.00
2	0.87	94.78	1.47	0.69	0.04	0.27	1.66	0.23
3	1.15	92.97	1.43	1.26	0.08	0.67	1.85	0.58
4	1.27	91.46	1.35	1.72	0.16	1.01	2.15	0.87
5	1.32	89.96	1.27	2.16	0.24	1.37	2.47	1.20
10	1.26	82.98	0.91	4.28	0.52	3.14	4.26	2.64
15	1.11	77.76	0.68	6.00	0.66	4.47	5.78	3.53
20	0.99	74.34	0.55	7.21	0.72	5.32	6.86	4.01

Variance Decomposition of Money Supply (M2)

Orthogonalized Shocks:

Period	IP	Stocks	M2	Prices	R	QS	EPU	S
1	0.02	8.02	91.96	0.00	0.00	0.00	0.00	0.00
2	0.14	7.43	86.91	0.51	0.96	0.06	1.33	2.67
3	0.08	10.28	74.77	0.83	3.92	0.08	2.29	7.73
4	0.12	12.35	63.85	0.83	6.80	0.36	2.42	13.28
5	0.21	13.73	54.58	0.67	9.17	1.00	2.19	18.45
10	0.47	14.69	27.81	0.77	14.57	6.61	0.81	34.28
15	0.36	12.44	17.11	2.82	15.05	11.48	1.57	39.15
20	0.26	10.55	12.29	4.88	14.54	14.41	2.85	40.23

Variance Decomposition of Prices (CPI)

Orthogonalized Shocks

Period	IP	Stocks	M2	Prices	R	QS	EPU	S
1	0.86	0.15	0.15	98.84	0.00	0.00	0.00	0.00
2	0.33	0.23	0.06	98.32	0.86	0.00	0.04	0.15
3	0.30	0.68	0.06	97.35	0.96	0.02	0.23	0.41
4	0.46	1.62	0.04	95.62	0.75	0.07	0.42	1.01
5	0.67	2.64	0.03	93.45	0.56	0.20	0.55	1.90
10	1.50	6.53	0.02	79.98	0.72	2.09	0.43	8.72
15	1.74	8.28	0.07	66.88	1.49	5.40	0.46	15.67
20	1.72	8.82	0.18	56.91	2.07	8.61	1.01	20.68

Variance Decomposition of Nominal Interest Rate (3 month)

Orthogonalized Shocks

Period	IP	Stocks	M2	Prices	R	QS	EPU	S
1	2.19	0.06	1.60	2.39	93.77	0.00	0.00	0.00
2	3.60	1.18	2.28	4.47	86.94	0.04	0.32	1.18
3	5.07	4.24	1.80	6.47	79.74	0.15	1.51	1.02
4	6.36	6.70	1.39	8.34	73.47	0.29	2.60	0.84
5	7.41	8.66	1.11	10.04	67.92	0.39	3.82	0.66
10	10.70	15.57	0.51	14.46	50.53	0.39	7.17	0.67
15	12.46	19.79	0.35	14.85	42.84	0.29	7.60	1.83
20	13.47	22.41	0.31	14.07	38.94	0.44	7.13	3.23

Variance Decomposition of Quality Spread

Orthogonalized Shocks

Period	IP	Stocks	M2	Prices	R	QS	EPU	S
1	1.58	11.75	0.34	1.51	0.30	84.52	0.00	0.00
2	2.76	17.00	0.19	3.03	3.67	72.58	0.72	0.06
3	3.25	19.93	0.15	3.32	5.46	66.49	0.94	0.47
4	3.57	21.04	0.12	3.43	6.71	63.21	1.05	0.87
5	3.75	21.66	0.10	3.47	7.58	61.02	1.09	1.33
10	3.89	21.99	0.05	4.01	9.70	56.07	0.74	3.55
15	3.62	20.83	0.03	4.97	10.33	54.64	0.45	5.13
20	3.35	19.70	0.03	5.86	10.49	54.17	0.34	6.06

Variance Decomposition of Economic Policy Uncertainty

Orthogonalized Shocks

Period	IP	Stocks	M2	Prices	R	QS	EPU	S
1	0.09	0.72	4.23	0.17	0.07	0.01	94.71	0.00
2	0.22	4.47	6.72	0.12	0.06	0.80	86.11	1.49

3	0.26	5.65	7.53	0.20	0.17	0.61	84.44	1.16
4	0.36	6.27	8.24	0.44	0.17	0.53	82.81	1.19
5	0.46	6.61	8.56	0.75	0.20	0.45	81.88	1.10
10	1.04	6.96	9.38	2.75	0.35	0.33	78.16	1.02
15	1.52	6.69	9.62	4.27	0.54	0.30	75.90	1.15
20	1.84	6.39	9.75	5.09	0.72	0.26	74.60	1.36

	Variance Decomposition of Sentiment							
	Orthogonalized Shocks							
Period	IP	Stocks	M2	Prices	R	QS	EPU	S
1	0.65	22.73	0.29	1.33	0.01	4.88	1.54	68.57
2	1.92	16.73	1.33	1.41	0.01	6.02	3.93	68.65
3	2.43	13.45	1.00	2.00	0.20	6.89	3.64	70.39
4	2.77	12.11	0.89	2.41	0.35	7.23	3.96	70.28
5	3.02	11.15	0.81	2.71	0.52	7.46	4.05	70.29
10	3.69	9.10	0.68	3.96	1.15	7.49	4.11	69.82
15	4.07	8.41	0.68	5.12	1.57	7.05	3.82	69.26
20	4.35	8.11	0.72	6.10	1.84	6.63	3.51	68.74

Figure 16: Response of Industrial Production to Shocks (Full Sample: March 1920 – December 1933)

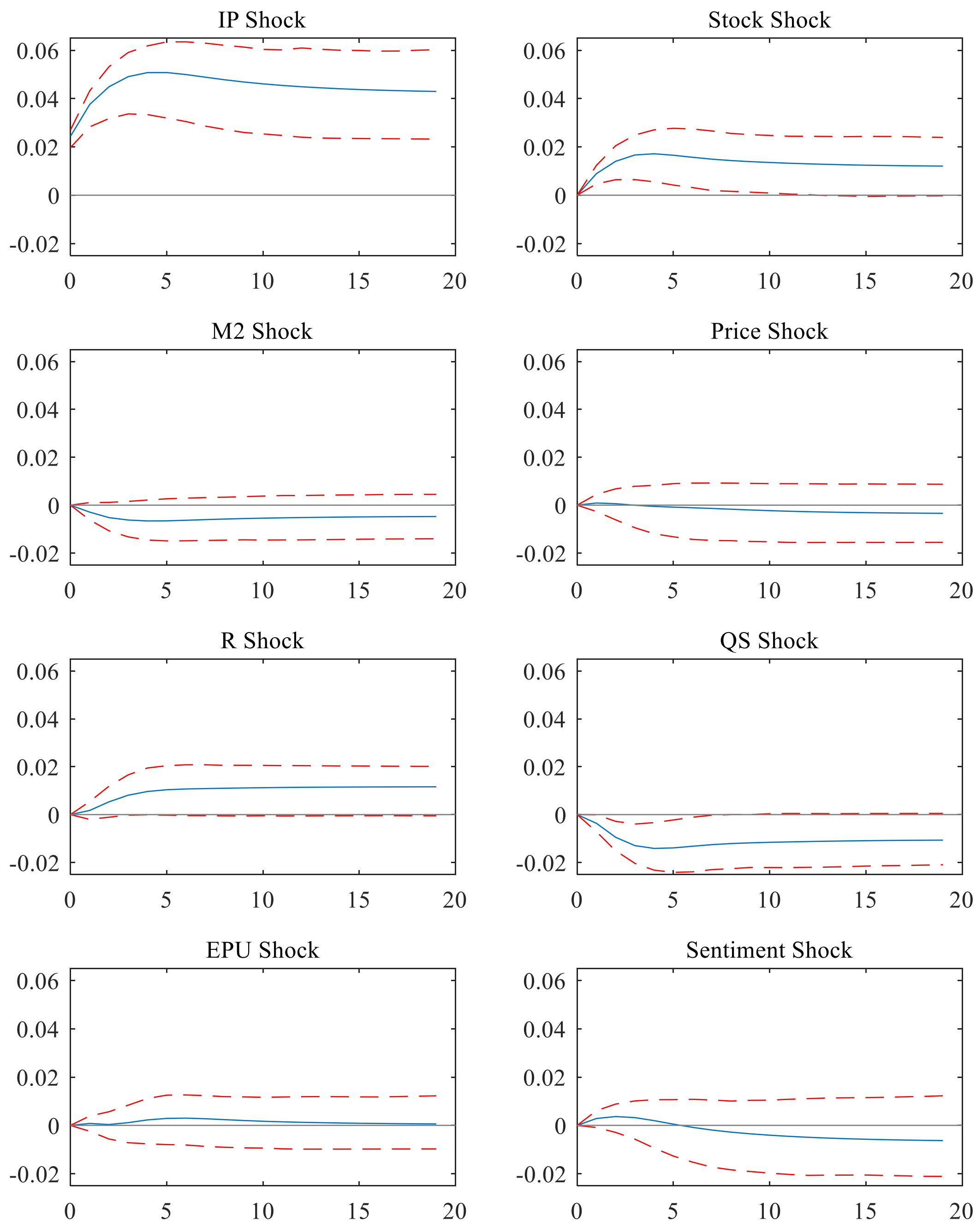

Figure 17: Response of Stock Market Index to Shocks (Full Sample: March 1920 – December 1933)

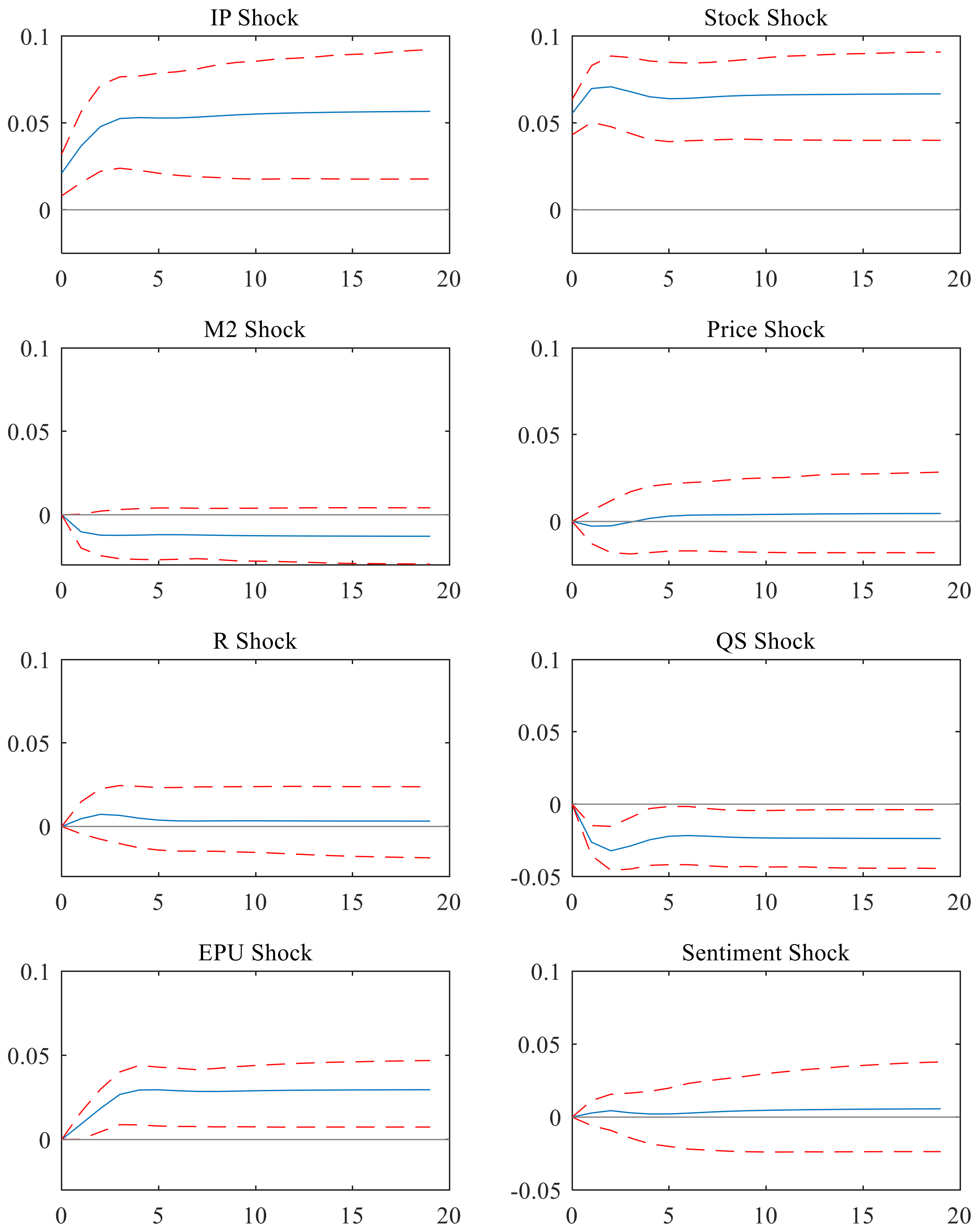

Figure 18: Response of Money Supply to Shocks (Full Sample: March 1920 – December 1933)

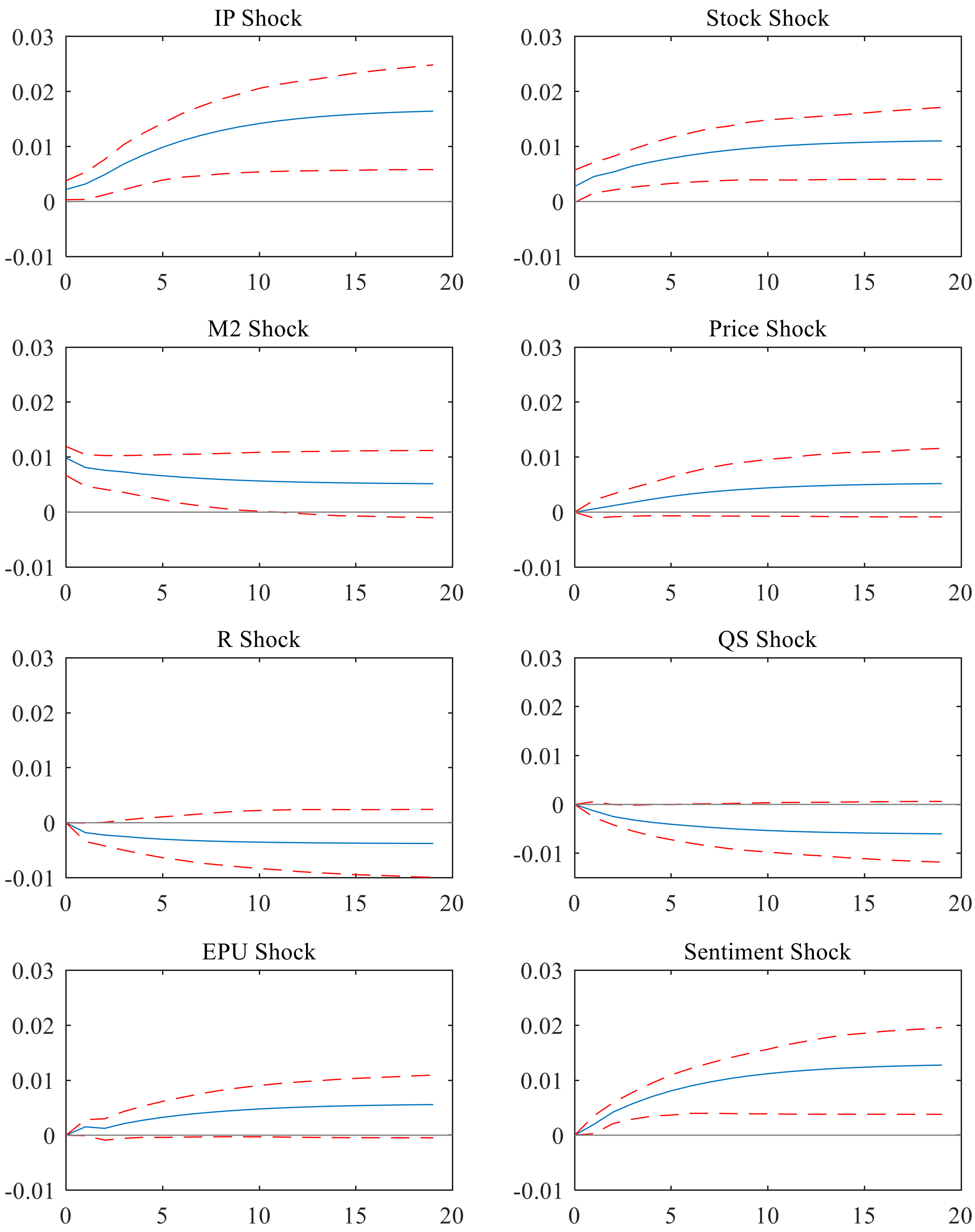

Figure 19: Response of Price Level to Shocks (Full Sample: March 1920 – December 1933)

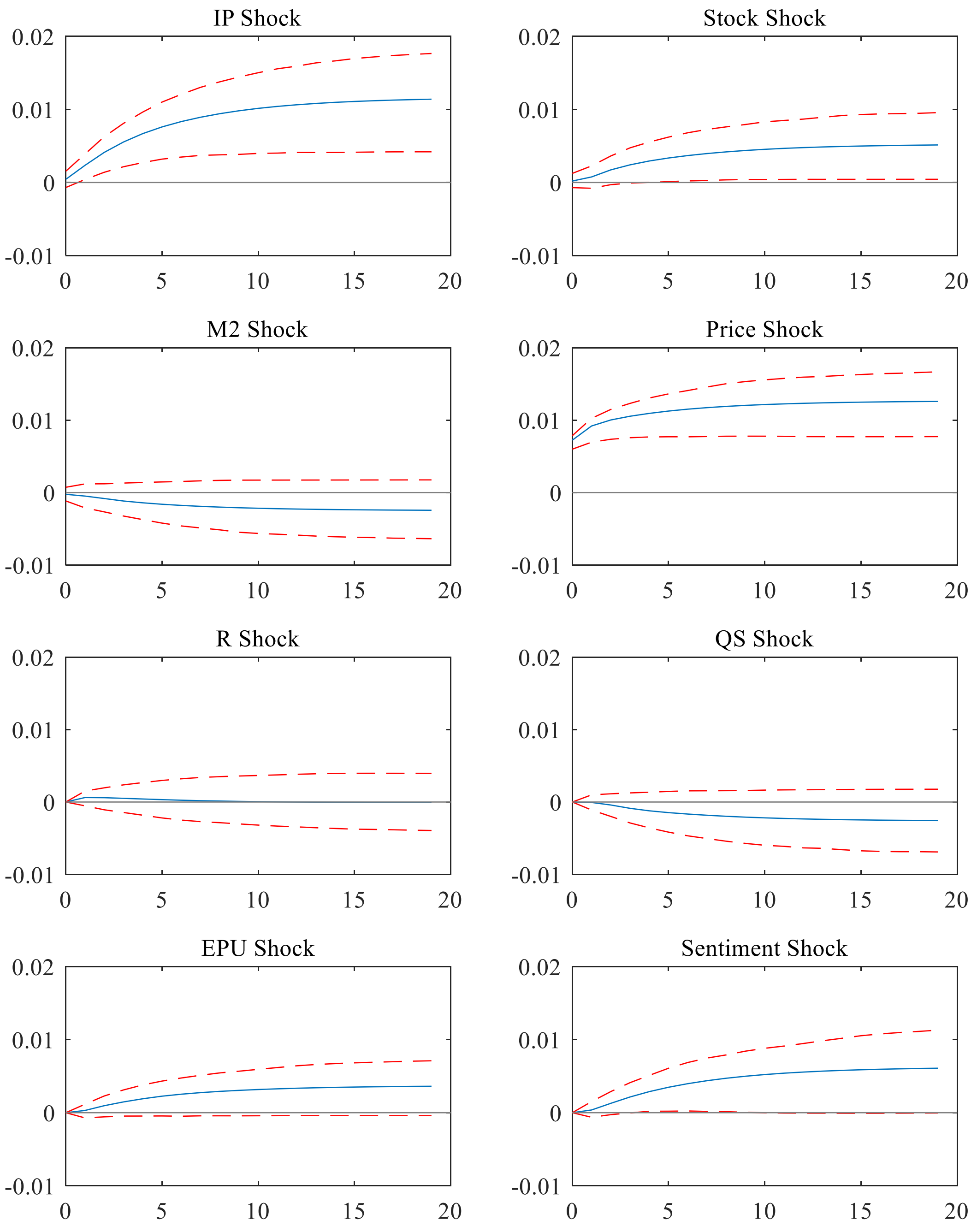

Figure 20: Response of Nominal Interest Rate to Shocks (Full Sample: March 1920 – December 1933)

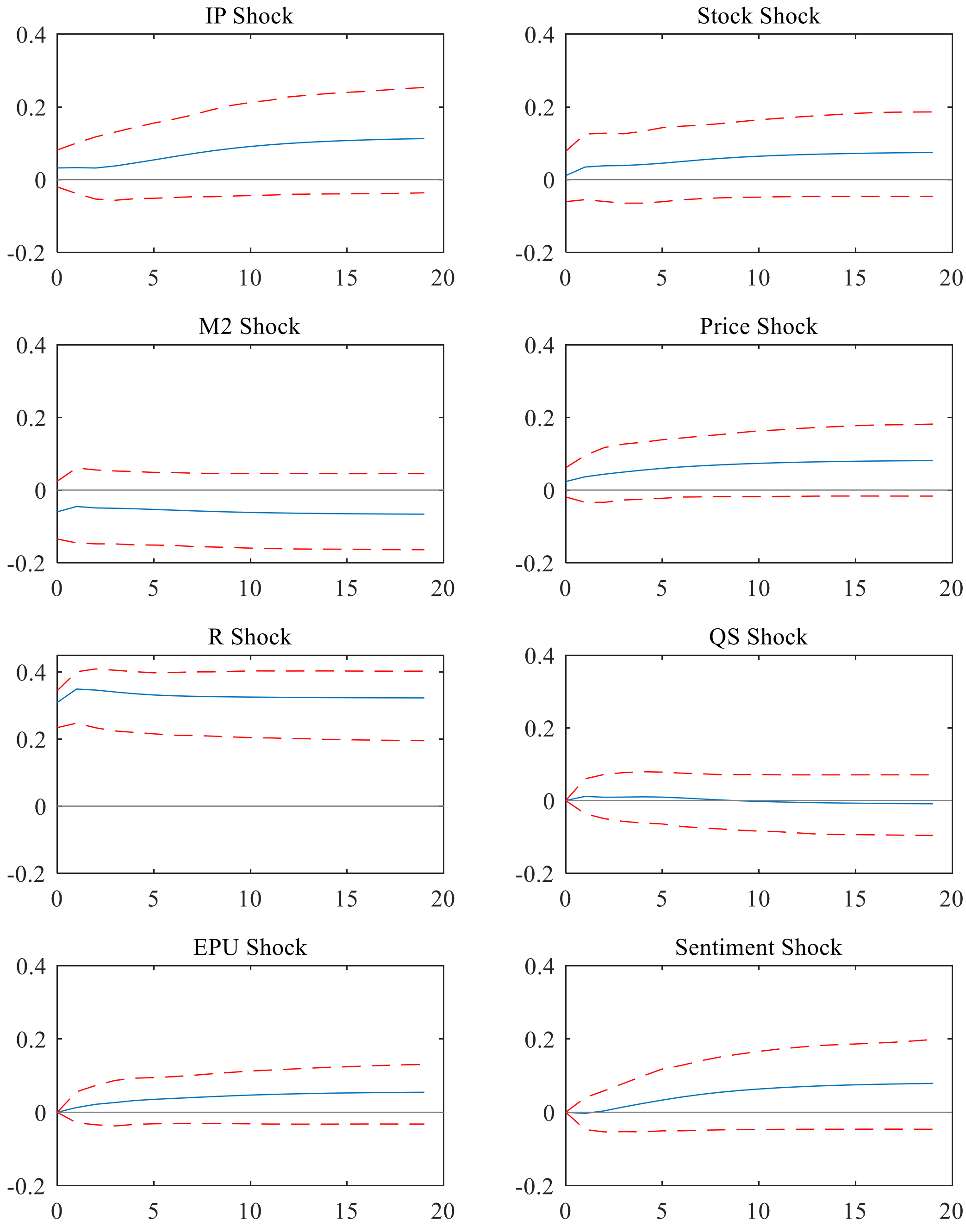

Figure 21: Response of Quality Spread to Shocks (Full Sample: March 1920 – December 1933)

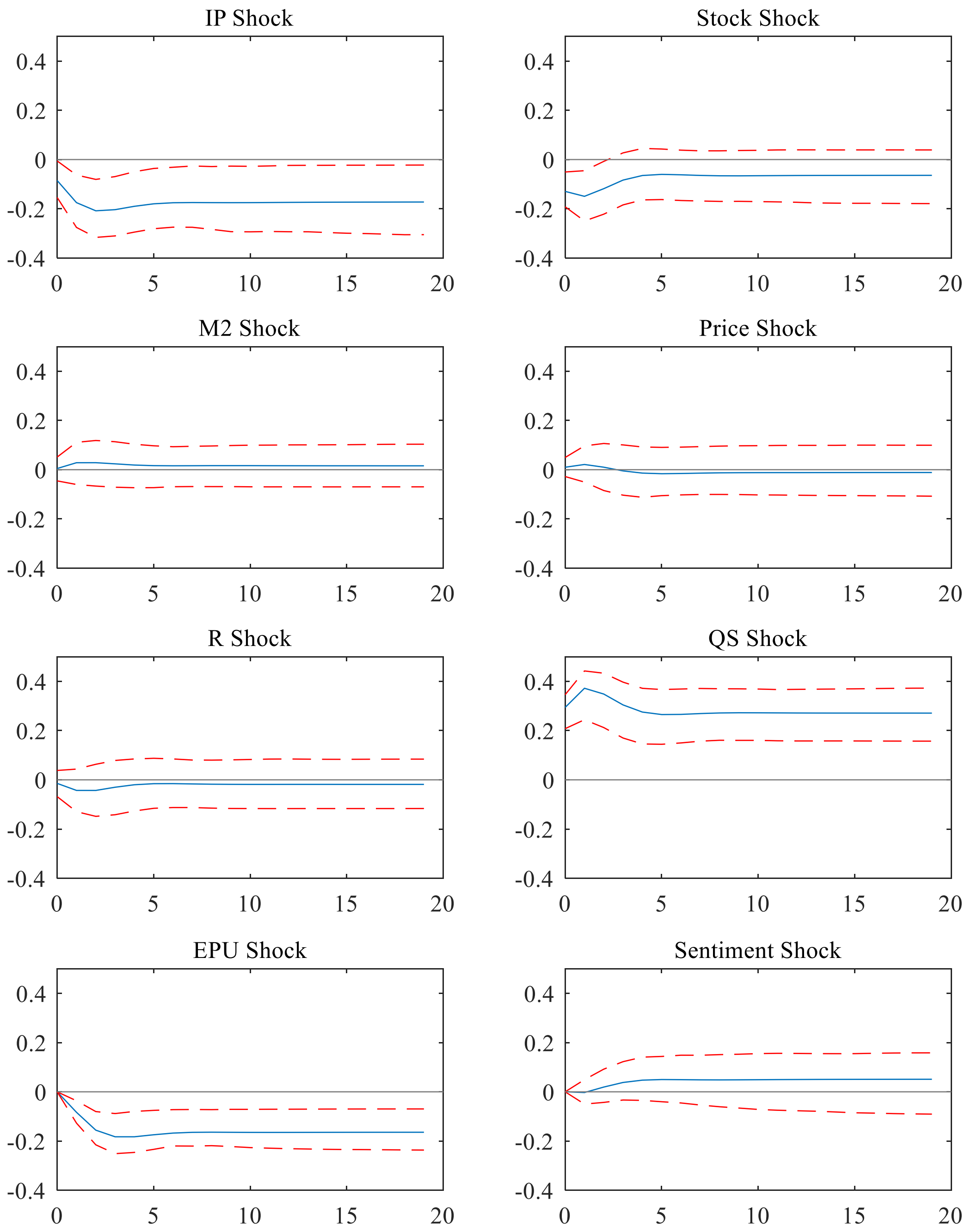

Figure 22: Response of Economic Policy Uncertainty to Shocks (Full Sample: March 1920 – December 1933)

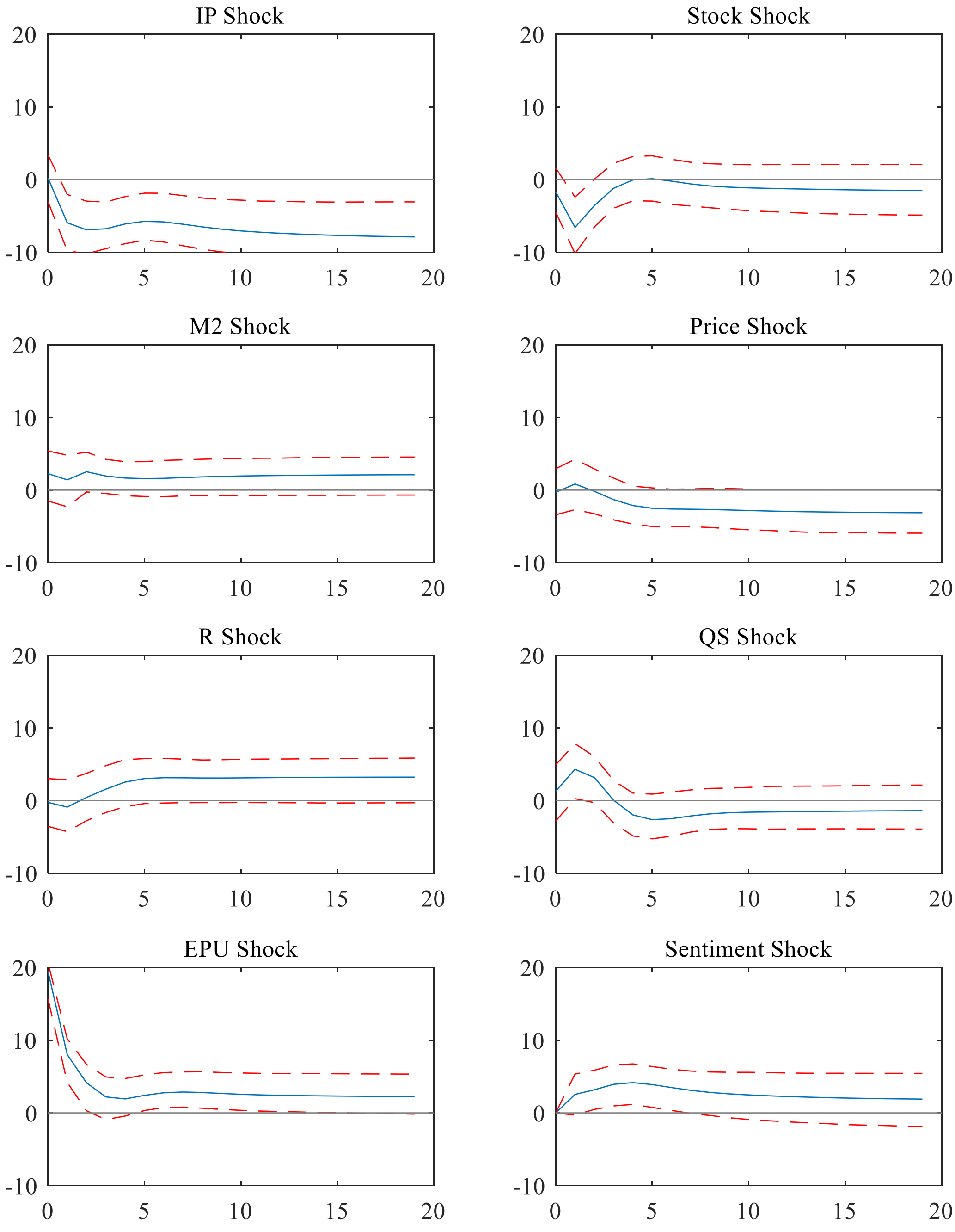

Figure 23: Response of Sentiment to Shocks (Full Sample: March 1920 – December 1933)

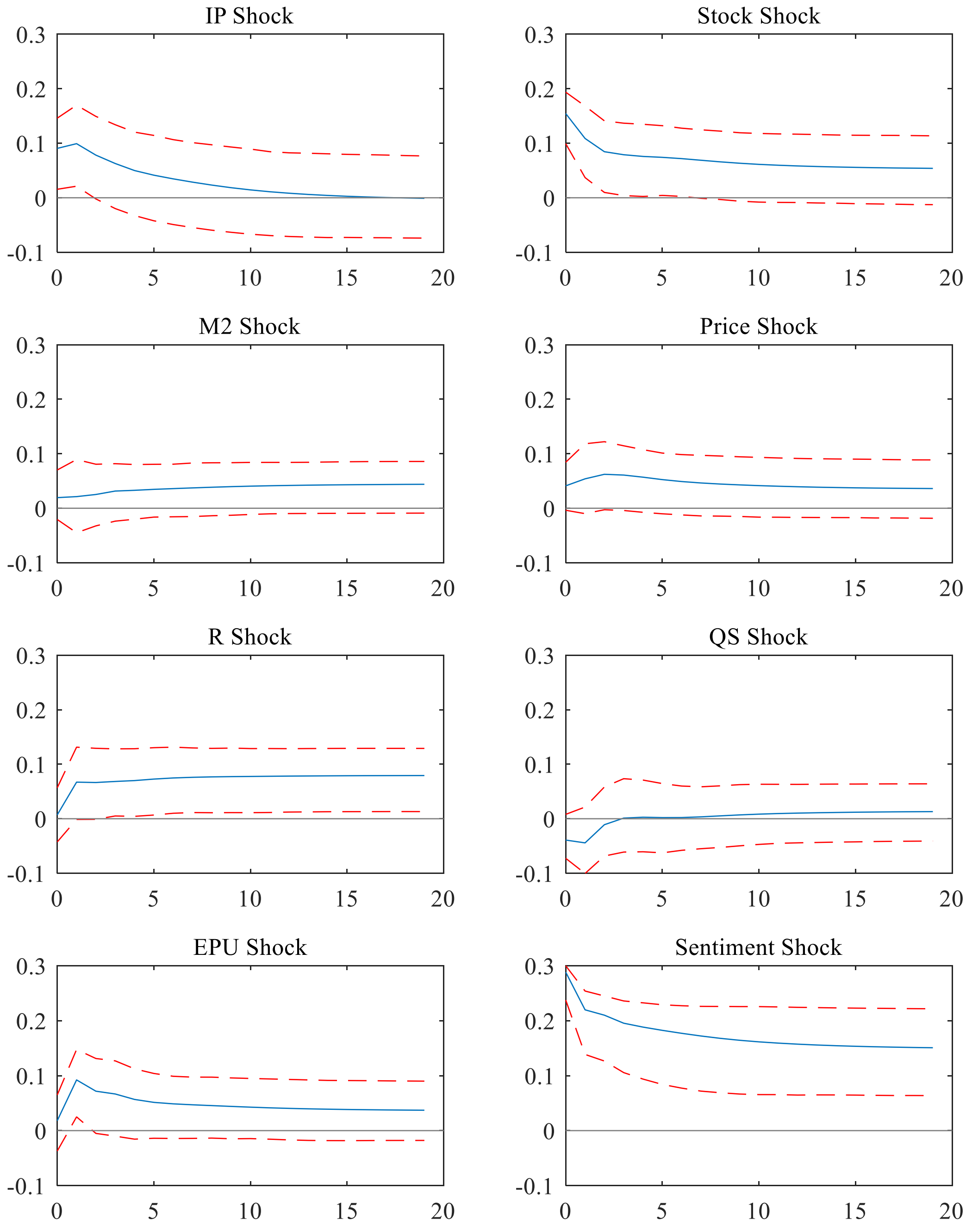

Figure 24: Response of Industrial Production to Shocks (1920s Sample: March 1920 – June 1929)

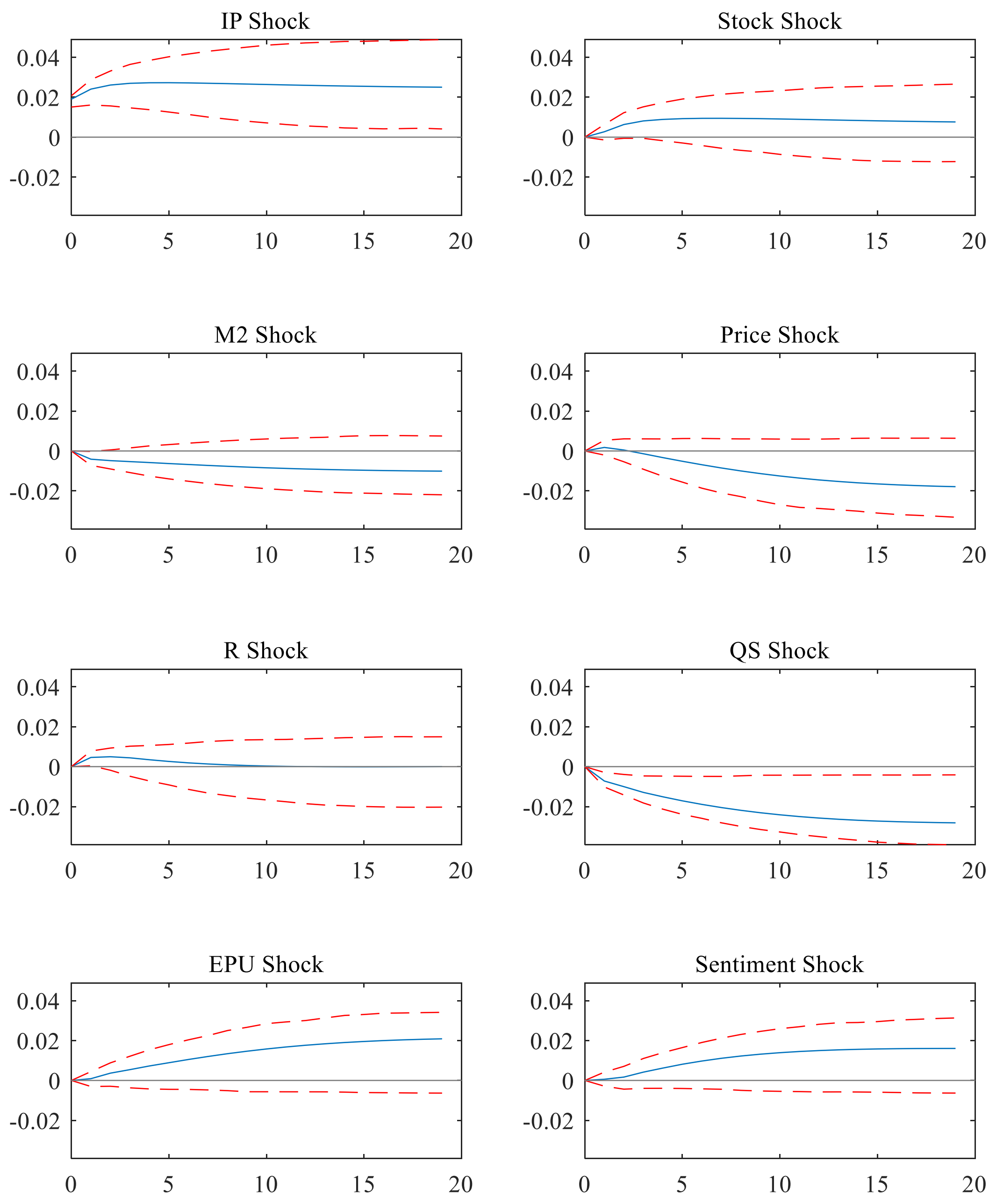

Figure 25: Response of Stock Price Index to Shocks (1920s Sample: March 1920 – June 1929)

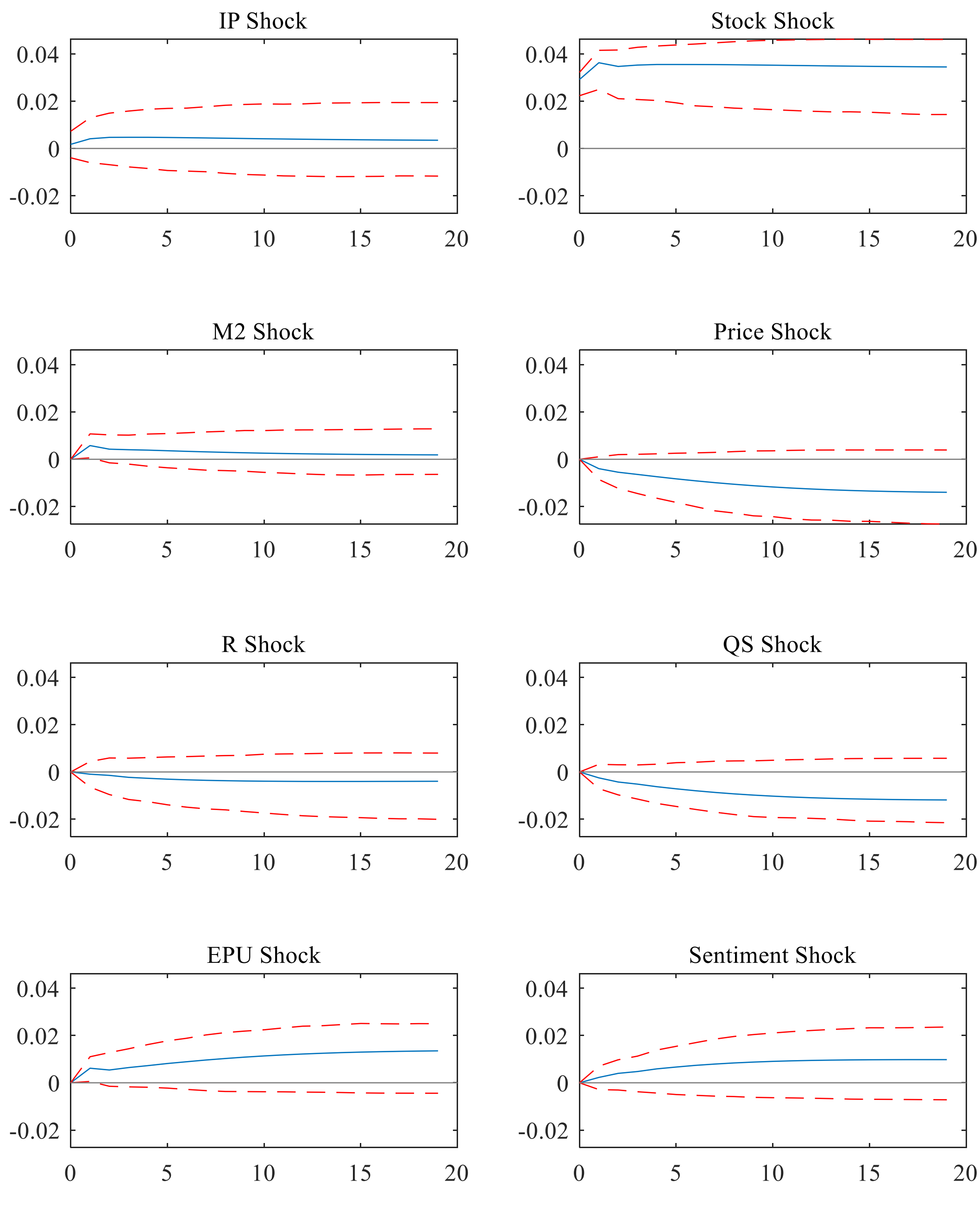

Figure 26: Response of Money Supply to Shocks (1920s Sample: March 1920 – June 1929)

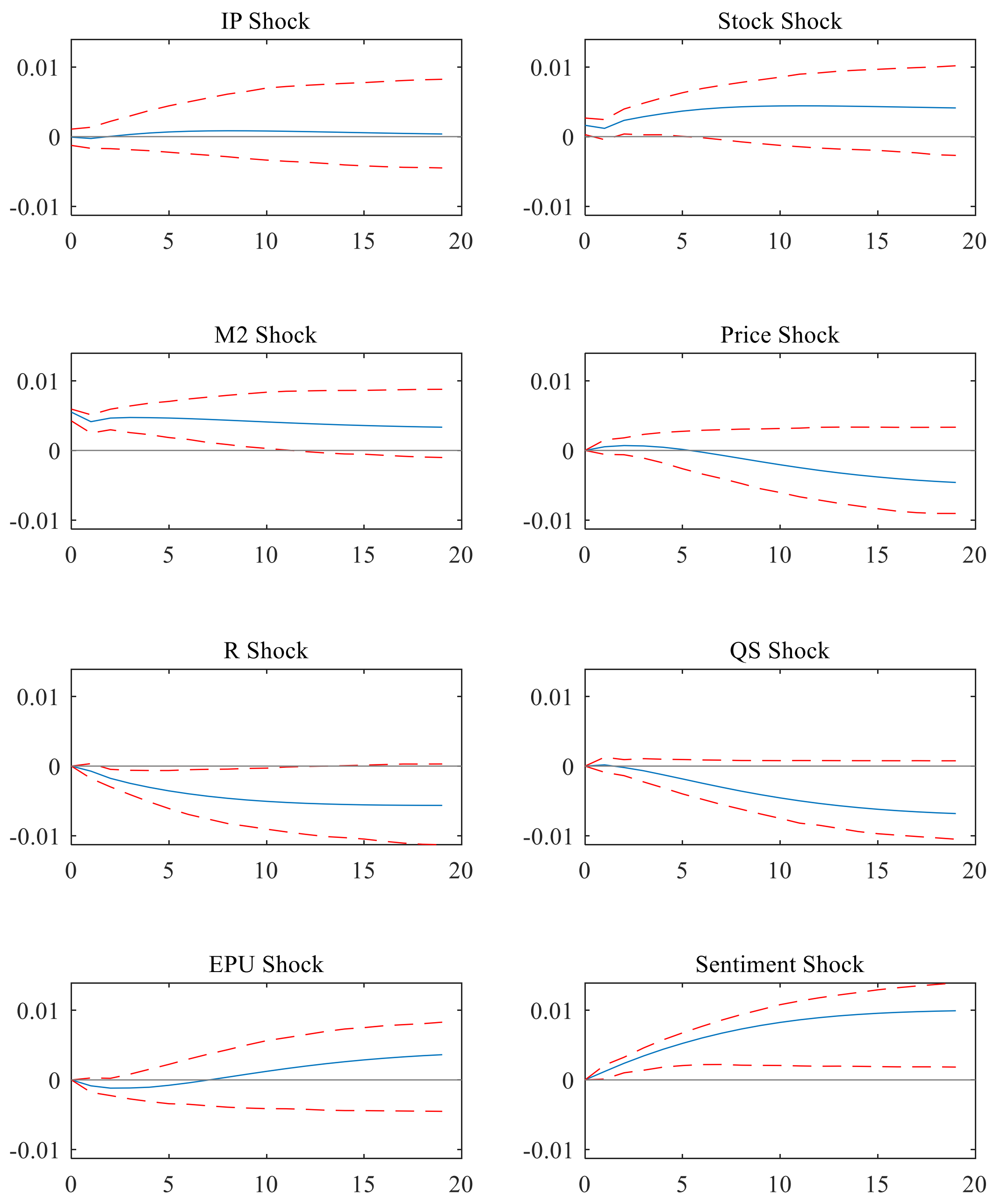

Figure 27: Response of Price Level to Shocks (1920s Sample: March 1920 – June 1929)

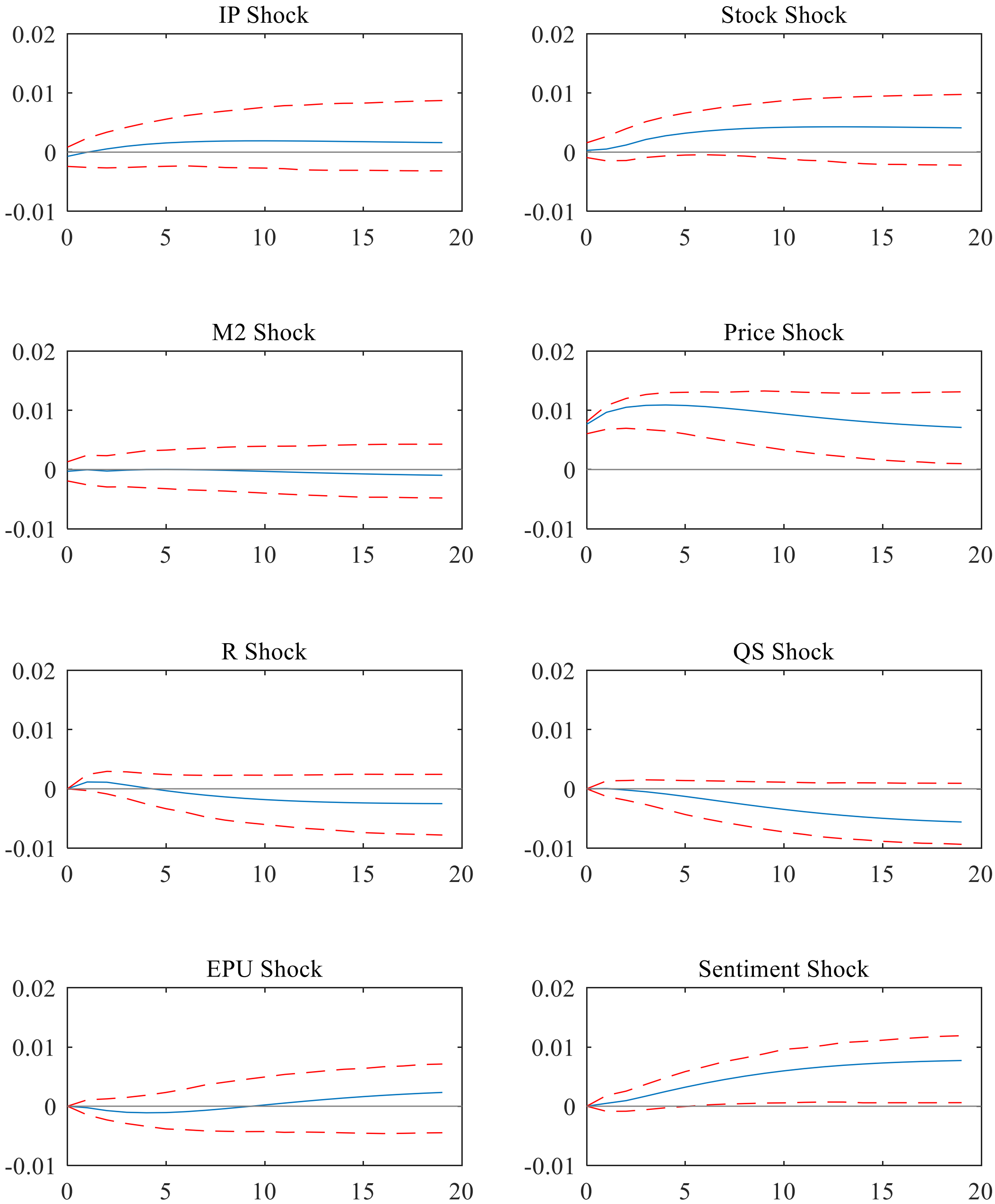

Figure 28: Response of Nominal Interest Rate to Shocks (1920s Sample: March 1920 – June 1929)

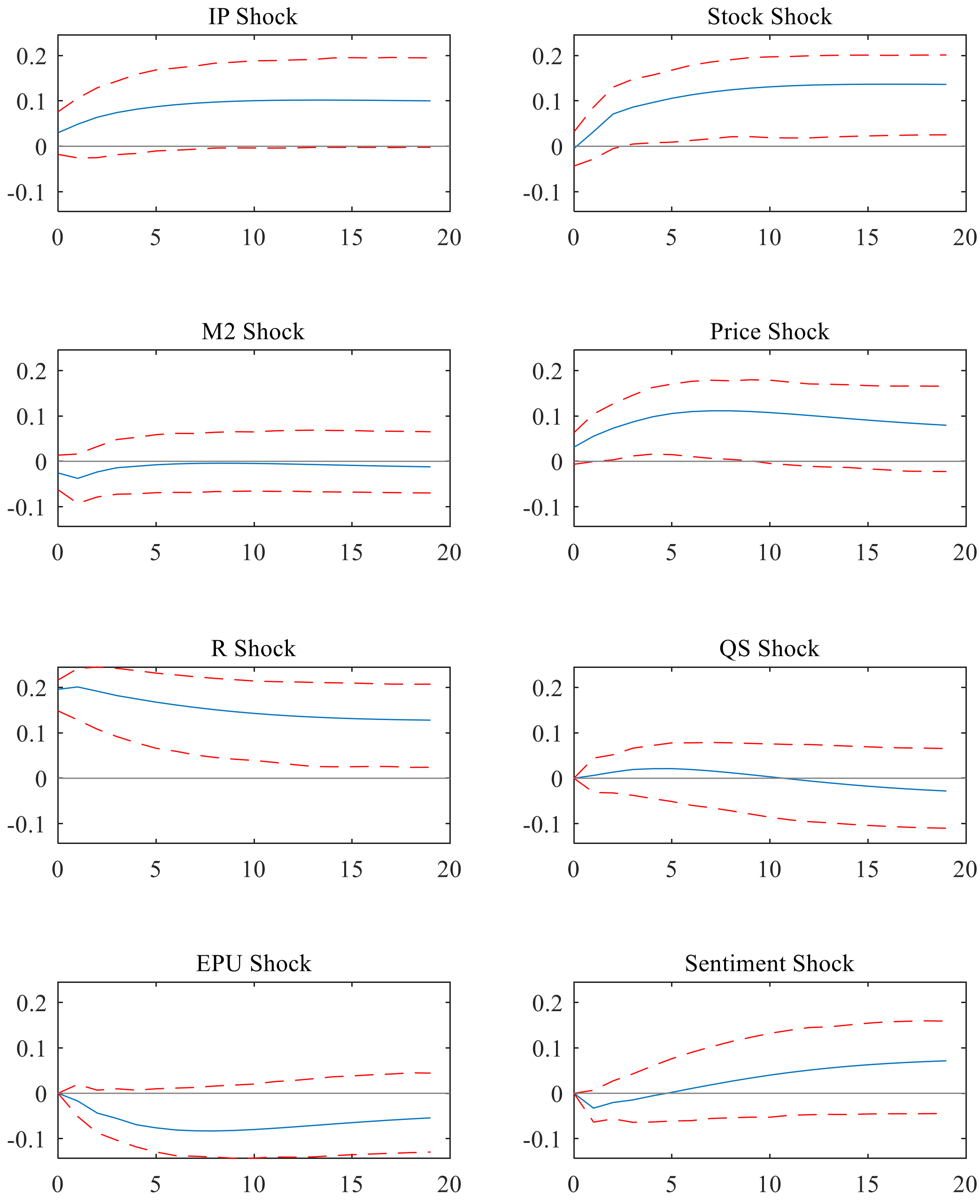

Figure 29: Response of Quality Spread to Shocks (1920s Sample: March 1920 – June 1929)

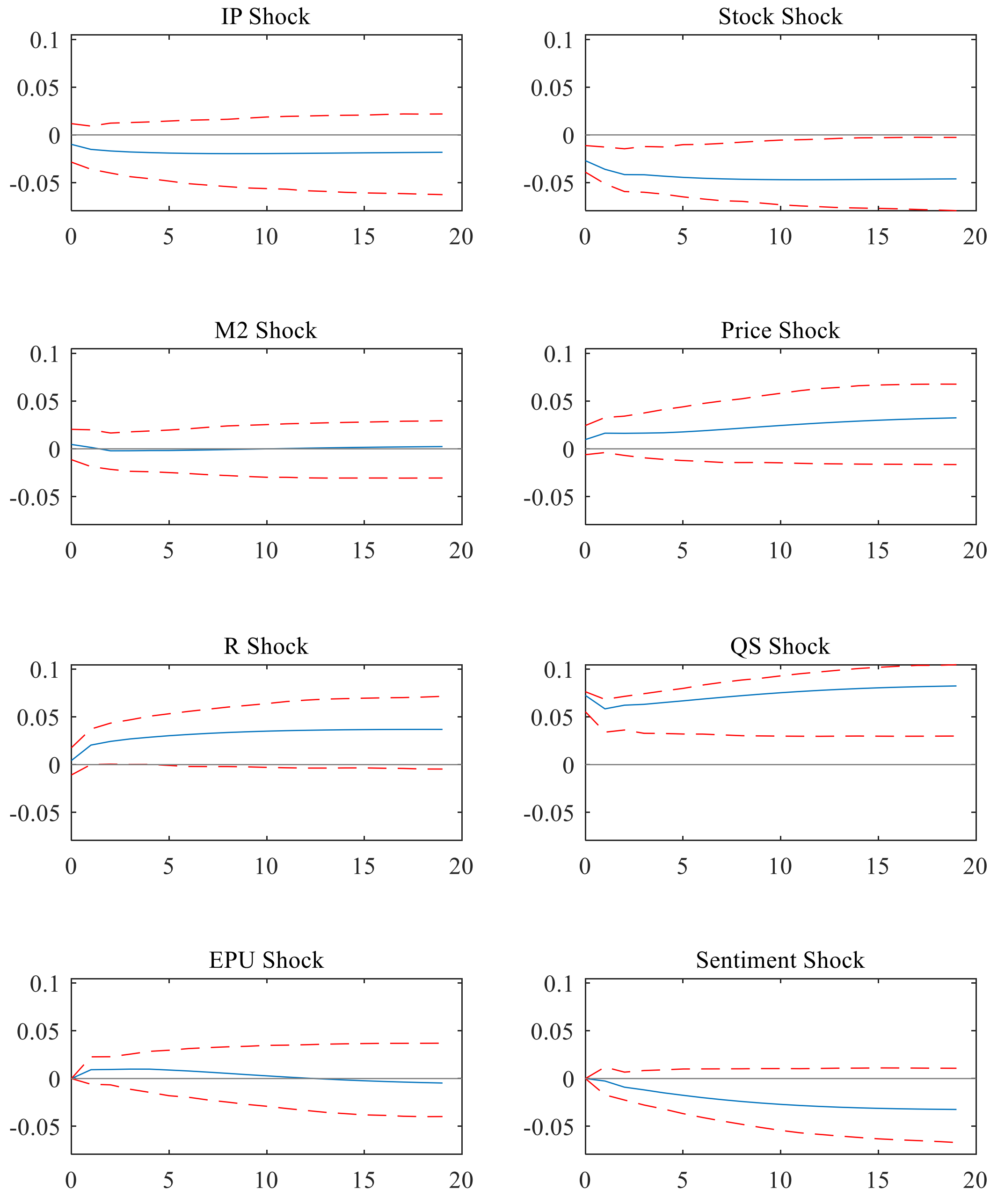

Figure 30: Response of Economic Policy Uncertainty to Shocks (1920s Sample: March 1920 – June 1929)

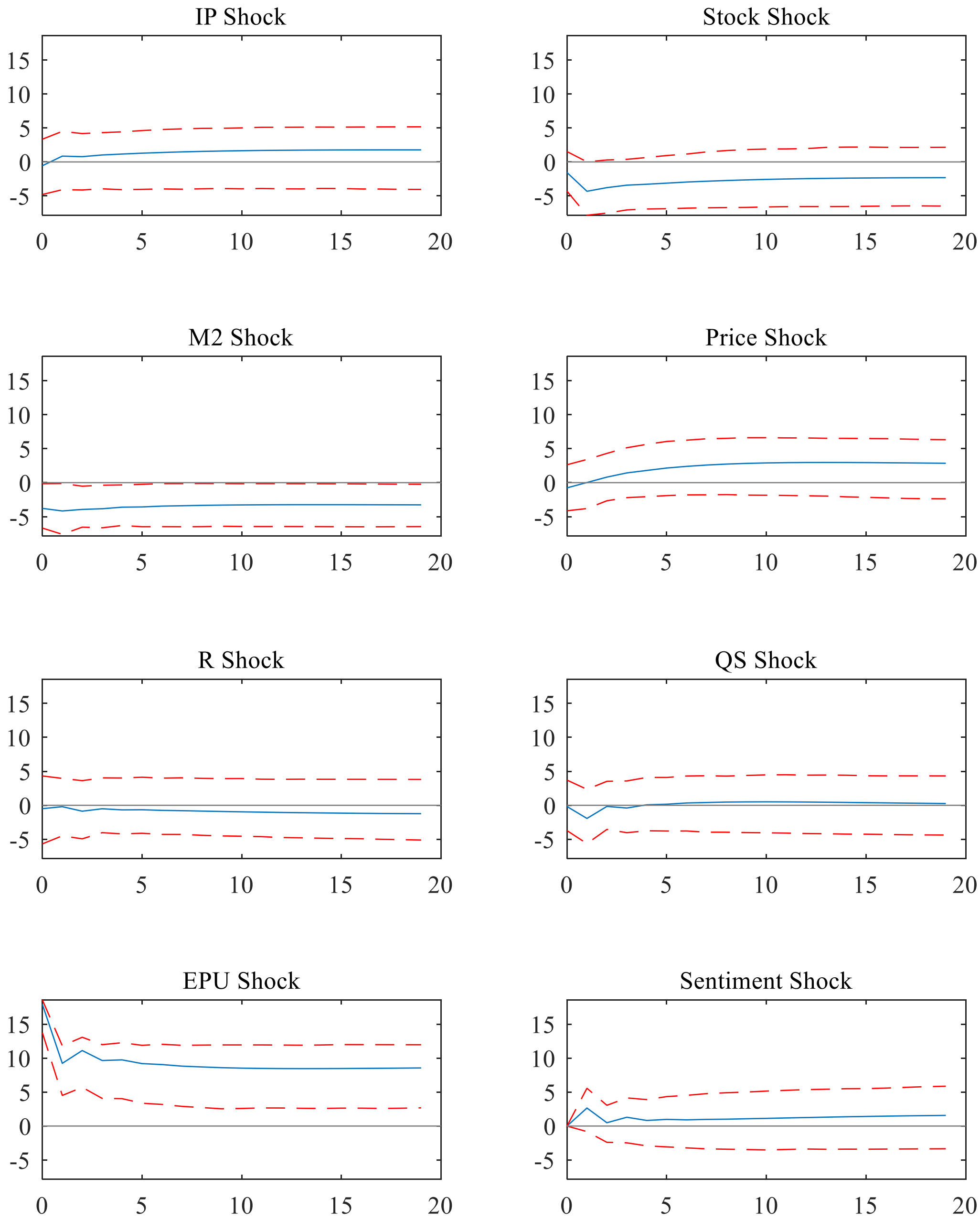

Figure 31: Response of Sentiment to Shocks (1920s Sample: March 1920 – June 1929)