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A Structural Analysis of Unemployment-Generating Supply Shocks with an Application to the US Pharmaceutical Industry

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Abstract

This paper aims to analyze unemployment-generating supply shocks. It proposes a structural vector autoregressive model estimated via a newly assembled identification scheme that relies on a minimum set of sign restrictions dictated by economic theory and recent market developments. We show that unemployment-generating supply shocks coexist with standard supply, demand, financial, and investment shocks, and we assess their impact on different macroeconomic variables. An application to the US pharmaceutical industry finds that the supply shock caused by Covid-19 in the sector is one of a kind. Particularly, the newly identified shock increases industrial production while decreasing the unemployment rate and producer prices in the US pharmaceutical industry.

Keywords: Supply Shock, SVAR,Pharmaceutical Industry, Macroeconomic Policy, Unemployment.
JEL Classification: E6, C11, C12, C22.

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1 Introduction

The escalating outbreak of Covid-19 affected one country's economy after another, attracting the attention of business leaders, policy makers, researchers, and ultimately the entire population worldwide. On the one hand, it significantly affected global financial markets, increasing the overall volatility and generating an unprecedented level of risk, which caused investors to experience huge losses in a very short time (Zhang et al., 2020). On the other hand, it precipitated enduring economic and social consequences, themselves enlarged by uncertainty about future developments, with governments toiling to formulate appropriate macroeconomic policy responses (McKibbin and Fernando, 2020). Moreover, the global crisis triggered by Covid-19 unfolded with unprecedented velocity, making the task of policymakers to assess its impact on the economy even more challenging, though necessary.

This complicated economic environment has offered, among other things, the opportunity to study a much broader phenomenon, i.e. supply shocks that generate unemployment. Prior work highlights that this kind of shock occurs when following an unexpected exogenous event, supplies change dramatically and triggers unemployment. (Nickell et al., 2004, Gertler et al., 2008). In more recent works Blanchard and Galí (2010) and Christiano et al. (2010) focus on unemployment dynamics in the presence of labor market frictions based on the New Keynesian model. Caggiano et al. (2014) analyzed unemployment dynamics during a crisis period via a Smooth Transition VAR. Nazaruddin et al. (2021) examine how the unemployment rate related to Covid-19.

However, while unemployment dynamics have received increasing attention and supply shocks are extensively studied by macro-economists, the two fields remain quite distant in recent literature. It is clear that unemployment is a key macroeconomic variable, but it is less clear how to identify which economic shocks cause it to change abruptly. Under extraordinary periods, unemployment changes can become difficult to predict across different sectors, yet this is a necessary task for properly handling future developments. While different studies highlight the extent to which economic shocks are transmitted to the labor market (Bachmann and Felder, 2017, Ribba, 2006), there are only speculations about which phenomena trigger unemployment dynamics. Thus, while informative about unemployment dynamics in different macroeconomic frameworks, much of the prior work remains vague on how to identify unemployment-generating supply shocks and apply them to specific situations.

The purpose of this paper is twofold: firstly, to analyze unemployment-generating supply shocks via a newly assembled identification scheme; and secondly, to provide an empirical application that can offer readers a practical example on how to apply our scheme to specific situations.

First, we propose our methodological contribution and we show how to identify unemployment-generating supply shocks. To this aim, a SVAR model will be estimated. To identify the model, we impose a minimum set of sign restrictions on the error terms. We argue that (positive) conventional supply shocks decrease the unemployment rate in the short run and that unemployment-generating supply shocks increase unemployment in the short run. We show that these shocks coexist with demand, financial, and investment shocks, and we assess their impact on Industrial Production, Producers Prices, Investments, Unemployment Rate, and Stock Prices. In our model, we have present five economic shocks that drive five variables, and therefore the system is fully identified.

Then, we propose an empirical contribution by pulling data from the US pharmaceutical industry. This sector, among others, underwent in some occasions the phenomenon we are researching, that is, unemployment was triggered following a supply shock. Particularly, we argue that this happened also during the years of the current Covid-19 pandemic. We show that the unemployment-generating supply shock played an important role in explaining the major fluctuations in industrial production, producer prices, and the unemployment rate in the US pharmaceutical sector. Particularly, the supply shock initiated by Covid-19 increased industrial production and decreased both producer prices and the unemployment rate.

Even if this phenomenon occurred in a number of sectors of the economy, we focus on pharmaceutical industry because it was a crucial reference for most governments worldwide. We argue that this industry is of utmost value from three points of view: social, economic, and financial. Pharmaceuticals have been the cornerstone of these unprecedented times, with the private sector offering support to governments , organizing isolation beds, deploying personnel in dedicated facilities, and investing a lot of money and effort to develop a vaccine against Covid-19. Accordingly, we can say that the pharmaceutical sector prompts a key social impact, not only because it saves lives but also because it can act as a facilitator for contract building between nations. As it relates to Covid-19, a recent study by Bartscher et al. (2021) shows that social capital and new infections and death are negatively related. Precisely, the authors demonstrated that a one-standard-deviation increase in social capital leads to approximately 34% fewer Covid-19 cases per capita, as well as between 6% and 35% fewer excess deaths per capita. This outcome serves as further evidence that the pharmaceutical industry acts in an environment that boosts social relationships and fosters collaboration between different players. It is also a very important economic contributor, as it employs over 6 million people and alone produces 5% of the US GDP (Rohrer and Pinard, 2021). Moreover, it is among the industries doing the most research and development, investing 6 times more than the average of all manufacturing industries (Rohrer and Pinard, 2021). Lastly, this is also interesting from the unemployment point of view. While the entire US economy was facing severe pressure with ever-increasing numbers of unemployment-benefit applications, the pharmaceutical sector did not and, in fact, saw employment increase. Nevertheless, once the Covid-19 emergency was over and the pressure relaxed, pharmaceuticals had to deal with the fallout of their showdown with their excess human resources. In fact, while they had to hire many experienced workers to face the Covid-19 emergency and develop a vaccine in no time, once the task was accomplished, all these workers were not needed anymore and decisions had to be made, which possibly lead to an increased unemployment rate in the industry. This relevance reflects on the capital market because data show that pharmaceutical companies tend to follow the economy generally. Referring to the stock market, we see that this industry alone accounts for 6.12% of the total US market capitalization. Lastly, this industry has a very peculiar capital structure, with, for example agreements with governments and permissions not usually afforded to industries due to the life-saving potential of its outputs.

The finding is that the supply shock triggered by Covid-19 is an example of unemployment-generating supply shocks, and it played an important role in explaining the major fluctuations in the US pharmaceutical macro-financial environment. Particularly, it was considerably important in explaining fluctuations in the industrial production, producer prices, and the unemployment rate. We deepened these findings by analyzing the impulse response functions of each variable to all the five shocks included in our model. The main result of this analysis is that the unemployment-generating supply shock increased industrial production and decreased both producer prices and unemployment rate. According to the model's predictions, this result should hold in the short run.

In the remainder of the paper: Section 2 presents our newly assembled identification scheme and the estimation of the structural vector autoregressive model; Section 3 proposes the application to the pharmaceutical industry, along with data and a structural analysis followed by an extended interpretation of results; and Section 4 concludes.

2 Supply Shocks and Unemployment Behavior

One of the most crucial puzzle in macroeconomics is explaining unemployment trends and the main source of its substantial shifts.

One of the very first contribution to the subject was presented by Phillips and others who developed the well-renowned Phillips Curve according to which wage inflation and unemployment rate are durably inversely related (Phillips, 1958, Phelps, 1967, Friedman, 1968). In a later work, Friedman and Phelps themselves criticized the Phillips Curve claiming that it was only a short run phenomenon and they developed the concept of the natural rate of unemployment. As a matter of fact, in the US in the Seventies, one of the first empirical evidence contradicting this theory took place when higher unemployment rates were not coinciding with lower inflation rates.[1] In a later work, Clarida et al. (1999) built on the classical ideas implementing various real world complications and derived the so-called New Keynesian Phillips Curve (NKPC), which was able to better capture the relation between inflation and unemployment. Since then, a heated debate populated the literature on the subject with alternative interpretations of the major factors rationalizing the long-run behavior of unemployment.

A branch of authors sides with the classical Keynesian idea that unemployment is a cyclical phenomenon and elaborations of this view. Among them, Nickell et al. (2005) propose an extensive empirical work studying unemployment patterns in the OECD countries from 1960 to 1990. They show that unemployment behaviors are mainly explained by shifts in labor market institutions. In their model, they also interact average values of these institutions with economic shocks and show that this adds no significant contribution to more accurately explaining unemployment trends. Building on the same theoretical framework, Benigno et al. (2015) show that, instead, it is the volatility in productivity growth that causes shifts in unemployment. In a recent work, Piluso and Colletis (2021) elaborated on the WS-PS models from a Keynesian point of view and show that in times of massive unemployment, the unilateral driver of employment are firms, on the basis of previous demand. [2] This result is criticized since it fails to reproduce unemployment volatility. Clerc (2021) suggested to adjust NKPC models introducing extensive and intensive margins. Guerra-Salas et al. (2021) build on this and add a richer labor market specification to a New Keynesian small open economy showing that the extensive margin of labor supply plays a major role in explaining and predicting labor market data. A interesting finding in this area is proposed by Campolmi and Gnocchi (2016). Developing a new Keynesian model with unemployment and endogenous participation, they show that stabilizing unemployment is desirable but not enough to stabilize employment. Bharadwaj and Dvorkin (2020) discuss on the reappearing of the Phillips Curve claiming that changes in the relative importance of supply and demand

[1] This phenomenon is called stagflation and it generally occurs when an economy undergoes a stagnant economic growth, rising unemployment and price inflation.

[2] WS-PS stands for Wage Setting - Price Setting curve. The Wage Setting curve determines the supply of labor, the Price Setting curve determines the demand for labor. The intersection point between these two curves represents the equilibrium unemployment rate (Layard et al., 1991).

shocks may lead to biased estimation of the Phillips Curve slope. They show that indeed the relation between unemployment and inflation is primarily determined by the relative importance of supply and demand shocks.

Building on these concepts, another branch of literature endorses the idea that unemployment is primarily driven by economic shocks and exogenous events. Bloom (2009) simulated a macro-uncertainty shock and showed that it generates a prompt fall and rebound in aggregate output and employment. Bloom explained that this happens since increased uncertainty brings firms about decreased investments and hiring. Nevertheless, in the medium run, the volatility triggered by the shock causes an overshoot in employment. It follows that uncertainty shocks generate short sharp recessions and recoveries.
Caggiano et al. (2014) studied the impact of uncertainty shocks on unemployment dynamics by way of Smooth-Transition VARs and highlighted that the effects of economic shocks on unemployment is better captured by nonlinear models.
Other studies, instead, still side with those claiming that unemployment is primarily pushed by economic shocks, but allege that demand shocks are the main drivers. Bukowski et al. (2008) show that positive labor demand shocks temporarily increase employment and that they are the main determinant of employment variability in the short-run. Travaglini and Bellocchi (2018) show that unemployment levels exhibit a relentless drop when hit by a positive demand shock. Borys et al. (2021) build a business cycle model and show that demand shocks explain at leas 58% of the variations in US unemployment and that the rest is driven by technology shocks.
On this line, part of the literature stands on the opposite side claiming that supply shocks are the main drivers of unemployment trends. Warne and Hansen (2001) use a common trends model with co-integration constraint and show that with unemployment being non-stationary, labor supply shocks are the leading cause that explains unemployment behavior. Ribba (2017) draws a similar conclusion. Adopting a structural VAR agnostic approach, he analyses the US postwar economy and shows that supply shocks have been playing a primary role in shaping the long-run unemployment evolution. Foroni et al. (2018) agree with this view and disentangle labor supply shocks from wage bargaining shocks, showing that these are decisive drivers of unemployment fluctuations in the short and long run. Billi (2020) elaborates on this results and show that when supply shocks are the main driver of fluctuations, employment targeting is optimal. These results are also supported by Diwambuena and Ravazzolo (2021). They show that labor supply shocks, together with wage bargaining shocks, are among the most important drivers of output and labor market variable across horizons.

In this paper, we side with this last branch of literature and find that supply shocks are major drivers of unemployment. In this section we present our model and its identification strategy.

2.1 Identification Strategy

The reduced form VAR model is specified as follows:

$$\mathbf{y}_t = \mathbf{c_B} + \sum_{i=1}^{P} \mathbf{F}_i \mathbf{y}_{t-i} + \boldsymbol{\mu}_t \tag{1}$$

where $\mathbf{y}_t$ is a $(N \times 1)$ containing all the N endogenous variables, $\mathbf{c_B}$ is a $(N \times 1)$ vector of constants, $\mathbf{F}_i$ for $i = 1, ..., P$ are $(N \times N)$ parameter matrices, P represents the number of lags, and $\boldsymbol{\mu}_t$ is the $(N \times 1)$ reduced form residuals with $\boldsymbol{\mu}_t \sim N(\mathbf{0}, \boldsymbol{\Sigma})$, where $\boldsymbol{\Sigma}$ is the $(N \times N)$ variance-covariance matrix. The model is then estimated using Bayesian methods and variables in levels. In this regard, we define diffuse priors, thus information in the likelihood is ruling.
To embed the error term of the model in (1) with economic meaning and hence perform policy analysis, some major modifications need to be applied. To cope with it, the dependent variable is multiplied by a non-singular parameter matrix $\mathbf{A}$:

$$\mathbf{A}\mathbf{y}_t = \sum_{i=1}^{P} \mathbf{B}_i \mathbf{y_{t-i}} + \boldsymbol{\epsilon_t} \tag{2}$$

where $\boldsymbol{B} = \boldsymbol{AF}$ and $\boldsymbol{\epsilon}_t \sim N(\boldsymbol{0},\boldsymbol{I})$, which can be interpreted as a combination of structural shocks i.e. innovations, and hence allows for economic analysis to be performed. Ideally, these shocks should be orthogonal and embedded with economic meaning. Fry and Pagan (2011) show that in any system of structural equations, retrieval of the structural equation parameters entails the use of identification restrictions, which shrinks the number of unrestricted parameters in the structural equations to a number that can be retrieved from the information in the VAR model, i.e. the reduced form. Equation (2) can be rewritten as:

$$\mathbf{y}_t = \mathbf{A}^{-1} \sum_{i=1}^{4} \mathbf{B}\, \mathbf{y}_{t-i} + \mathbf{A}^{-1}\, \boldsymbol{\epsilon}_t \tag{3}$$

From (3) one derives that $\mathbf{F} = \mathbf{A}^{-1}\mathbf{B}$ and $\boldsymbol{\mu}_t = \mathbf{A}^{-1}\boldsymbol{\epsilon}_t$ where $\boldsymbol{\Sigma}_\mu = \mathbf{A}^{-1}\mathbf{A}^{-1}$. Since $\mathbf{F}$ and $\boldsymbol{\Sigma}_\mu$ are known from the estimated reduced form VAR in (1), if $\mathbf{A}$ is pinned down, also $\mathbf{B}$ and $\boldsymbol{\epsilon}_t$ can be calculated with $\mathbf{B} = \mathbf{AF}$ and $\boldsymbol{\epsilon}_t = \mathbf{A}\boldsymbol{\mu}_t$. Therefore, structural economic shocks can be thought as linear combinations of the reduced-form VAR innovations. Accordingly, to identify the structural autoregressive model, $\mathbf{A}$ needs to be found and a first reasonable guess would be starting from the variance of $\boldsymbol{\mu}_t$, i.e. $\boldsymbol{\Sigma}_\mu = \mathbf{A}^{-1}\,\mathbf{A}^{-1}$. An identification problem occurs since the number of unknowns exceeds the number of the equations. To solve this issue, some restrictions needs to be imposed on $\mathbf{A}$. Since this matrix is symmetric, $N(N\text{-}1)/2$ restrictions need to be identified to derive $\mathbf{A}$, with N being the number of endogenous variables.

The literature for identification procedures is very rich and present many different options. The most straightforward and widely used system to impose restrictions on $\mathbf{A}$ is the Cholesky decomposition, i.e. imposing zero short-run restrictions. Ljung (1981) explains that with this identification procedure some elements of $\mathbf{A}$ are assumed to be 0 since it is considered to be a lower-triangular. Rigobon and Sack (2003) show that when considering financial variables and multiple shocks, like in the case of this research, zero restrictions are inappropriate and, therefore, other identification procedures need to be followed. Another common way to impose restrictions on $\mathbf{A}$ is imposing a minimum set of sign restrictions on the structural shocks, i.e. $\boldsymbol{\epsilon}_t$. As introduced by Furlanetto et al. (2017) this identification procedure works particularly well when the number of variables included in the matrix equations and the number of economic shocks are large, like in this case. [3] A detailed explanation of this

[3]The estimation is conducted in MATLAB version R2020 using the parallel function over a 12-core machine with 3.55 GHz. The estimation is completed in 72 hours for models with five identified shocks

procedure follows in the next section.

2.2 Sign Restriction Analysis

In this section, we firstly state how a minimum set of sign restrictions has been be imposed as well as why this is key to the success of this research. Secondly, we provide the output of this analysis, along with some literature justifying these choices.

2.2.1 Sign Restriction Imposition Technique

As stated in the previous section, sign restrictions on $\boldsymbol{\epsilon}_t$ are one of the ways literature presents to identify the non-singular parameter matrix A and hence identifying the SVAR model in (2). Even if this identification procedure might be computationally challenging, it is key to the success of this research since it allows to impose a priori a certain number of sign restrictions on the structural shocks so that a certain direction is enforced. This eases the computational procedure and embeds shocks with some economic directional meaning suggested by economic theory and recent market developments.
To integrate the sign restrictions we use the methodology introduced by Rubio-Ramírez et al. (2010) and applied by (Furlanetto et al., 2017) as well, which fits particularly well in this context. First, we rewrite $\mathbf{A}^{-1}$ as $\mathbf{A}^{-1} = \mathbf{P}^{'}\mathbf{S}^{'}$, where $\mathbf{P}^{'}$ is the Cholesky decomposition of $\boldsymbol{\Sigma}_{\mu}$ and $\mathbf{S}^{'}$ is an orthonormal matrix which follows a multivariate normal distribution and has mean an NxN matrix of zeros and variance an N^2xN^2 identity matrix.This generates uncorrelated shocks corresponding to a precisely identified model. Second, we seek to find $\mathbf{S}^{'}$ since once it is found, A can be derived. Consequently, the equation for $\boldsymbol{\epsilon}_t$ can then be rewritten as:

$$\boldsymbol{\epsilon}_t = \mathbf{P}^{-1}\mathbf{S}^{-1}\boldsymbol{\mu}_t \tag{4}$$

Combinations of these shocks are formed following two steps. Firstly, a QR decomposition of $\mathbf{S}$ is performed. Secondly, candidate impulse responses are generated. [4] If these generated impulse responses satisfy the theory-driven sign restrictions presented in the next section, the impulse responses are stored. Otherwise, a new matrix $\mathbf{S}$ is drawn and the procedure is repeated until the theory-driven sign restrictions are satisfied. These restrictions are imposed only on impact, in keeping with the recommendation of Canova and Paustian (2011).

2.2.2 Theory-Driven Sign Restrictions

Having stated the imposition technique, we now specify which theory-driven sign restrictions we enforced.

Consistently with the three-equation New Keynesian model, supply shocks are set to increase output and to decrease prices in the long run (Straub and Peersman, 2006). The effect of a standard supply shock on investment/output, and on the stock market index are left unrestricted since unclear. Consequently, the unemployment rate must be the variable that allows to separately identify unemployment-generating supply shocks from standard supply shocks. We argue that conventional supply shocks decrease the unemployment rate in the short run and that unemployment-generating supply shocks increase unemployment in the short run by their very nature.

[4] The QR decomposition is a mechanism used in linear algebra to decompose a matrix A into a product of an orthogonal matrix Q and an upper triangular matrix R. In statistics and econometrics, this technique is often used to solve the OLS problem.

Table 1: *Table showing the sing restrictions used for each variable to each shock. NA indicates that the response of the variable is left unrestricted. The orange cells indicate the uniquely identification of shocks.*

Theory-Driven Sign Restrictions in the Baseline Model

	Supply 1	Supply 2	Demand	Investment	Financial
Industrial Production Index	+	+	+	+	+
Producer Prices Index	-	-	+	+	+
Investment/Output	NA	NA	-	+	+
Unemployment Rate	-	+	NA	NA	NA
Stock Market Index	NA	NA	NA	-	+

Similarly, demand shocks are set to increase both output and prices in the long run (Carlin and Soskice, 2005). The effect of a demand shock on the unemployment rate and on the stock market index is unclear and is left unrestricted. Since output is expected to grow more than investments, we impose that a positive demand shock has a negative effect on investment/output. This variable differentiates a demand shock from an investment shock since demand and investment shocks imply the same sign restrictions on output and prices (Corsetti et al., 2014). It follows that an additional variable is needed to uniquely identify demand and investment shocks, i.e. investment/output. WEassume that investments shocks are driven by investments and, accordingly, investments should grow more than the output itself. Moreover, we assume that investment shocks generate an investment boom. For these reasons, we argue that a demand shock and an investment shock have a negative, i.e. a positive effect on investment/output respectively in the short run.
Literature shows that financial shocks and investment shocks imply the same restrictions on output, prices, and investment/output (Justiniano et al., 2010). The effect of a financial shock on the unemployment rate is unclear and, therefore, it is left unrestricted. Accordingly, an additional variable is needed to separately identify investment and financial shocks. To this purpose, we have built a dedicated stock market index including the 10 biggest public companies by market capitalization in the sector of analysis. We argue that an investment shock negatively triggers this index, while a financial shock positively. This financial shock is treated as a conventional demand shock. It is to be underscored, though, that this is sector-specific. For reasons explained in the next section this is the case for the pharmaceutical industry, but it should be rethought and adjusted to the specific application and sectors.

3 Empirical Application to the US Pharmaceutical Industry

Since Covid-19 outbreak, its effects on the worldwide economy have been widely analyzed by economists, financial risk managers, and governments. As a matter of fact, its extraordinary features along with its extensive consequences on the economy and on societies across the world have raised an ever-increasing attention. Nevertheless, significant research has yet to be conducted to quantify its impact on financial markets, asset classes, and sectors to understand what the major drivers of recent financial fluctuations were. This chapter aims at providing a review on the literature existing so far to compare its results with those achieved in this research.
Most literature available focuses on analyzing the shock triggered by Covid-19 as compared

to past infections to understand which revitalization techniques were adopted at the time. Some recent studies proved that the 1918 Spanish flu was in nature very similar to Covid-19. It had a very high infection rate, i.e. of 30% of the world population, and fatality rate, i.e. of 10% of infected cases (Yi et al., 2020). Additionally, both infections occurred over three major waves hitting one geographic area after another and recurring with similar features in every country. The geography of the phenomenon was a little different though. After breaking out from Wuhan, Covid-19 engulfed most of the globe, firstly hitting South Korea, Singapore, and Hong Kong, then hitting Iran, and other parts of South East Asia, and lastly reaching the United States, the United Kingdom, and most of Europe. In this regard, it is worthwhile to mention that not every country responded to Covid-19 in the same way. In fact, some countries appeared to have arrested the exponential growth of infections better than others, i.e. Hong Kong, Singapore, South Korea, and Japan, which might be due to strong universal health care and state capacity (Acharya, 2020). Instead, 1918 Spanish flu burst from the United States, then spread through North America, Central and South America, West Africa, and Russia, and hit Australia and Europe at last (Cape, 2017). Moreover, in 1918 there were no pharmacologic options and governments resorted to social distancing measures as well (Acharya, 2020). According to some studies, countries where multiple interventions of different nature were adopted at an early stage, showed peak death rates approximately 50% lower than those that did not and performed flatter epidemic curves, and 20% lower cumulative excess mortality (Hatchett et al., 2007). This result is surprising since very few cities implemented non-pharmaceutical interventions for more than 6 weeks. Particularly, the closure of schools, churches, and theaters was connected to lower peak death rates. Nevertheless, no single intervention could be connected with improved aggregated outcomes for the first wave of the 1918 Spanish flu (Hatchett et al., 2007). This provided historical support to the argument that there was not a big trade-off between economic activity and public health, since it was necessary to suppress the virus to enable consumers to be more confident and for businesses to operate on their standards (MarketWatch, 2020). Similar circumstances were observed under Covid-19 crises since it is a commonplace to state that beginning March 2020 until late 2021, almost every government undertook rigorous extreme measures such as targeted lockdowns and stay-at-home orders. However, it is intersting to underline that a recent study by Cronin and Evans (2021) shows that these unmitigated policies, including total shutdowns and targeted restrictions, had little effect on promoting social distancing compared to social responsibility.

It follows that the two infections are closely related, yet unlike for many other aspects.

One remarkable difference is the age distribution of fatalities. In fact, some recent studies have proved that the elderly were overwhelmingly the worst hit under Covid-19, whereas during the 1918 Spanish flu the young working-age people were the most harshly affected. Indeed, in 1918 the US death rate due to influenza amongst 25-43-year-olds was more than 50% higher than the one of 65-74-year-olds (Shanks, 2020). A second key divergence lies in the sociopolitical contexts of the two infections' worlds. In fact, the globalized society of 2020 is much more interconnected than the one of 1918 and it is known that people travel around the world much faster and with a higher frequency. It is interesting to underline that exactly this interconnection was the main cause for the Spanish flu to spread all over the world. In fact, World War I and soldiers' mobilization created a perfectly suited environment for influenza to disperse and even if the origin of 1918 Spanish Flu are still obscure, evidence shows that moving soldiers were the main driver of its circulation (Hannoun, 1995). It follows that the historic period during which 1918 Spanish flu unfolded plays an important role. In

fact, due to the impact of World War I, regardless of the mass fatalities affected by Spanish Flu, the subsequent economic contraction was of minor magnitude. This is the case since the demand produced by the war effort enhanced economic recovery in a way that cannot be compared to today's environment (Velde, 2020). This mitigated economic impact is also explained by the differences in the economic structures of 1918 and 2020. In fact, at the time employment was concentrated in natural resources and mining and was mainly located in nonmetropolitan areas where the population density was lower. Nowadays, most of the jobs are situated in urban areas, which are also the most highly populated. Accordingly, the 2020 environment could enable Covid-19 to spread at a higher pace as it would have in 1918 and triggered larger economic damage (Basco et al., 2020).
From this analysis it emerges that even if the two infections seem closely related, it is important to be aware of the major differences to avoid confusion and misinterpretation of economic measures undertaken by authorities and governments.
Additional significant literature analyzes the crisis triggered by Covid-19 as compared to 2008 global financial crisis to understand financial markets responses. It is claimed that most financial crises follow similar patterns, i.e. they originate with a shock, they continue with financial systems being impacted with short-term debt rollover problems, increase in financing costs, and credit crunch and they end leaving uncertainty, i.e. market volatility, unpredictable policy responses, and huge model risk (Bordo and Landon-Lane, 2010). Covid-19 yielded similar features if compared to 2008 global financial crisis. In fact, it caused high leverage in certain sectors of the economy along with global spillovers through the financial sector. Nevertheless, for many other aspects it is deeply different. Firstly, during 2020 Covid-19 crisis, households and balance sheets of the banking sector were in a better state as compared to 2008. Secondly, during 2020 Covid-19 crisis the aforementioned global spillovers were directed to the real economy rather than to financial sectors first and, consequently, there was a sudden stop to real activity rather than via financial amplifiers. Lastly, financial markets crashed at the very beginning of Covid-19 crisis, which is comparable to peak levels during 2008 global financial crisis. Moreover, there are also some major differences in global financial markets. In fact, not all sectors, i.e. asset classes were impacted with the same magnitude (Sansa and Hasan, 2020). Market data show that in April 2020 stocks rallied, but that earlier in the Covid-19 crisis, the global equity market experienced a meltdown. Stocks plummeted amid dreads of the disease's outbreak and its impact on the global economy, sometimes to the point that trading was completely frozen. Nevertheless, in June 2020 US equity performed positively, enlarging the gap between markets and economic data. Specifically, large market-capitalization stock indexes plunged around March but performed increasing patterns afterwards. Instead, gold and the major market-capitalization-weighted bond indexes were almost unaffected. Business performances also differed deeply across sectors. Internet and Direct Marketing Retail stocks were the best-performing showing an increase of 17.2%, whereas Energy stocks were the worst-performing, with its price decreasing by 40% since January 2020 (Ramelli and Wagner, 2020). In the very framework of this research, it is worth to comment on the pharmaceutical stocks' performance. Data show that their performance increased by 8.2% from April 2019 to April 2020, whereas it decreased by almost 2% from the beginning of the year. This aspect will be reclaimed when commenting on the performance of pharmaceutical stock prices later in this research.
Even if the effects of Covid-19 on the worldwide economy have been widely analyzed by economists, financial risk managers and governments, much research has yet to be conducted to quantify its impact on the different sectors to understand what the major drivers of recent

market fluctuations are. With this paper, we take a step further in filling this gap with the qualifying contribution of our work being the rigorous strucutural econometric analysis. In fact, to the very best of our knowledge, while a lot of narrative is available in literaure, no macroeconomic approach has been undertaken with the ultimate goal of understanding the drivers of recent market fluctuations.

3.1 Data Description

In this chapter, the data employed for the empirical application will be depicted. Firstly, it will be described how the dataset has been composed and what each variable represents. Secondly, the number and the nature of the structural shocks will be identified.

3.1.1 Data Treatment

The pool of variables employed in this research is in line with a rich literature that aims to quantify the effect of economic fluctuations. Past studies show that when structural shocks are studied, it is key to include some macro-financial variables depicting the whole economic environment as well as some variables that are directly related to the studied phenomenon, i.e. shock (Kilian and Lütkepohl, 2017). It is also important to select variables that allow to separately identify each related shock.

The dataset assembled for this research comprises 5 US quarterly time series, covering the period that goes from the second quarter of 2000 to the last quarter of 2020. Most data were gathered from the FRED database, FitchConnect web portal, and IBISWorld industry reports.

The data series used for the estimation of the model explained in detail in the following sections are summarized in Table A.1 in Appendix A. For more information on each of them, see Figures A.1, A.2, A.3, A.4 and A.5 in Appendix A.

The first series considered is composed by the output, i.e. industrial production in the US pharmaceutical sector. For consistency reasons, the index expressing industrial production relative to the base year 2012 was chosen over the absolute dollar value of the production. This index is periodically published by the Federal Reserve Board (FRB) and it is obtained by aggregating values from government agencies and industry associations using the Fisher-Ideal formula.[5]

The second series considered comprises prices, for which the Producer Price Index for the US pharmaceutical sector was selected. This index indicates the average change in selling prices from domestic production over time relative to a base year, in this case 1984. It represents one of the oldest continuous systems of statistical data periodically published by the Bureau of Labor Statistics and also one of the eldest economic time series assembled by the Federal Government.

The third series is composed by the investments made in the US pharmaceutical sector. To better perform economic analysis, the ratio between these investments and the industrial production, i.e. the first series, was considered. The idea behind this series is to gain insight on how much government and private investors invested in this sector over time as a percentage of the overall sector production volume. This is particularly interesting for the pharmaceutical sector since oftentimes the output does not correspond to the amount of

[5]The Fisher-Ideal formula is such that preserves only information related to growth, i.e. normalizes the dollar industrial production values.

capital invested. In fact, huge investments are usually made to timely produce a single drug or medicament, which, though, happens to be sold at a regulated price (Lakdawalla, 2018). The quarterly investments in the US pharmaceutical sector were not directly available and, therefore, had to be derived. Firstly, the annual investments in the US pharmaceutical sector were downloaded from FitchConnect. Precisely, this series included all the funds mobilized by government and private systems for the US pharmaceutical sector according to the WHO. Secondly, the quarterly private nonresidential fixed investment series was downloaded from FRED, which can be considered a generic measure for investments. At this point, the logarithmic growth of this series was computed to be able to match the two series and obtain the quarterly value of investments in the pharmaceutical sector. To do so, a system of four equations shown in (5) and four unknowns was built:

$$\begin{cases} x + y + z + h = Ye \\ ln(y/x) = ln(IQ2/IQ1) \\ ln(z/y) = ln(IQ3/IQ2) \\ ln(h/z) = ln(IQ4/IQ3) \end{cases} \tag{5}$$

with *x,y,z,h* being the investments in the US pharmaceutical sector in the first, second, third, and fourth quarter, respectively and *IQ1, IQ2, IQ3, IQ4* representing the quarterly private nonresidential fixed investments. At this point, the system, i.e. the equations to find the pharmaceutical investment in every quarters, is solved. Consequently, the quarterly series of the investments in the pharmaceutical sector could be generated.
The fourth series considered comprises the unemployment rate in the US pharmaceutical industry. This information is monthly published by the U.S. Bureau of Labor Statistics and includes every experienced private wage and salary worker that is at least 16 years old. This variable has been selected since during the current Covid-19 crisis, unemployment reached its highest peak in the US. In fact, as of March 2020, more than 3 million Americans filed for unemployment benefits, which is more than 3 times higher compared to 2019. Nevertheless, as explained in the following sections, the situation in the pharmaceutical sector might have been completely different. In fact, it is reasonable to assume that an increased number of talented and skilled workers was hired to develop effective medicaments and, possibly, a vaccine. Accordingly, unemployment in the pharmaceutical sector in the first quarter of 2020 might have shrunk. For this reason, this variable was considered a distinguishing feature of the current Covid-19 crisis and it was included in the analysis.
The fifth and last series considered in this research is a stock market series, i.e. a specifically constructed index comprising the biggest pharmaceutical companies in the United States. Even if there are a couple of indexes available for the pharmaceutical sector, such as the ones presented by S&P or Dow Jones, they are quite recent and are only available since 2005. Accordingly, an index was specifically built for the aim of this research. This was done starting from a selection of 11 pharmaceutical companies presented in a recent industry report by IBISWorld. The selction of companies considered along with their market capitalization, and the weight each of them has been assigned is shown in Table 2 below. Consequently, the quarterly stock prices of each company were download and weighted for the market capitalization of each company in order to obtain a weighted average stock price for each quarter. We deemed important to include Moderna in the analysis due to its main role in developing an mRNA vaccine. Nevertheless, since it exists only since 2019, we weighted it accordingly. For detailed information about the selection of companies, please refer to Table A.3 in A.

Table 2: *Table summarizing the companies included in the specifically built stock market index. Data were retrieved on May 13th, 2021.*

*billion of $	Market Cap	Weight
Johnson & Johnson	$ 318.11	24.59%
Pfizer Inc.	$ 208.25	13.44%
Merck & Co., Inc.	$ 195.01	12.58%
Abbott Laboratories	$ 158.28	10.21%
Eli Elly & Co.	$ 141.52	9.13%
Bristol-Myers Squibb Company	$ 136.48	8.81%
Gilead Sciences, Inc.	$ 91.79	5.92%
Stryker Corporation	$ 69.93	4.51%
Regeneron Pharmaceuticals, Inc.	$ 61.34	3.96%
Biogen, Inc.	$ 48.28	3.12%
Moderna, Inc.	$ 57.57	3.72%
	$ 1549.56	100%

3.1.2 The Number of Shocks and their Nature

Besides being necessary to specify the SVAR model, determining the number of shocks also has an intrinsic economic interest. Economic theories disagree about the exact number of shocks that drives the economy. In fact, literature splits in two major schools of thought. On the one hand, early real business cycle models believe that there is only one supply shock driving economic fluctuations. On the other hand, new Keynesian Dynamic Stochastic General Equilibrium (DSGE) models argue that there are at least ten shocks driving the economy (Forni and Gambetti, 2010). [6] In this research, five different economic shocks will be considered, which is in line with the number of variables previously explained. Particularly, the approach employed by Furlanetto et al. (2017) is closely followed.
Broadly speaking, every economic shock can be categorized as either demand or supply driven, depending on the correlation of output and prices.
In this research, supply shocks are intended to be expansionary, i.e. positive, and hence to increase output and reduce prices. Two different supply shocks are considered, i.e. supply1 and supply2. The former is a conventional positive supply shock in the pharmaceutical sector, which will be intended as the need to produce more medicaments. The latter is the economic shock caused by Covid-19 in the pharmaceutical sector, which will be intended as the need to develop and market a vaccine against flues or viruses causing pandemic events. In fact, the rapid expansion of this virus worldwide yielded an increased supply, with pharmaceutical companies being under pressure to develop a new vaccine. From a macroeconomic point of view, though, it is not clear if the shock caused by Covid-19 is more a demand or a supply shock. Some recent literature argues that this crisis initially triggered a supply shock, which was then revitalized by the central banks' interventions. Next, it caused a demand shock, which, instead, remained unresolved since, as history shows, it usually takes longer for these kinds of phenomena to recover. Accordingly, it is possible to argue that this crisis affected both sides, i.e. both supply and demand (Brinca et al., 2020). Nevertheless, since it originated as a supply shock, in this research the shock triggered by

[6] DSGE stands for Dynamic Stochastic General Equilibrium. Through econometric models, this technique seeks to explain major economic phenomena, such as economic growth and business cycle, as well as the effects of economic policy

Covid-19 will be treated as a supply shock.
Similarly to supply shocks, demand shocks have been considered to be expansionary, i.e. positive, and hence to increase both output and prices. Particularly, these shocks refer to the shortage that the US pharmaceutical sector experienced during the crisis triggered by Covid-19. Indeed, according to recent statistics, increased hospitalization, and demand for assigning patients to ventilators, contributed to a prescription medicine shortage, i.e. price rise, which was further enlarged by the so-called panic-buying. [7] On global levels, most regulatory authorities declared that the pharmaceutical goods that were experiencing the higher demands were potential Covid-19 treatments associated to pneumonia. Specifically, the impact on medicine shortage fluctuated based on access levels, retail and hospital-only, and type. Among these, medicines used in hospitals to treat Covid-19, that is sedatives, respiratory and pain treatments registered a growth of 100% to 700% since the beginning of the year (Ayati et al., 2020). Accordingly, it can be claimed that the pharmaceutical sector experienced a major positive demand shock, which will lead to considerable price increases in the long run.
A rich literature underlines that investment and financial shocks can be treated as demand shocks since they move output and prices in the same direction (Fornari and Stracca, 2013). Specifically, investment shocks are shocks to the supply of capital in the pharmaceutical sector. Accordingly, they induce a negative co-movement between investment/output in the pharmaceutical sector and the price of capital, represented by the stock market index. In the context of this research, these shocks represent the fact that pharmaceutical companies have performed an extraordinary behavior as regards investments. As a matter of fact, during current Covid-19 crisis, many leaders of operations in the pharmaceutical industry have been highly responsive, rallying to facilitate the supply of key drugs across borders, handle the workforce safety, and managing the unfolding government restrictions, while starting to set basis for new vaccines and therapeutics (Martin and Bowden, 2020). This kind of activity required outstanding investments, which was most likely encouraged by the FED supportive actions.[8]
It is important to highlight that these shocks, though similar, are separately identified in this research thanks to the sign restrictions imposed on the different variables and explained in section 2.2.
For a brief description of the aforementioned shocks, please consult Table A.2 in Appendix A. An in-depth description of the impact of each one of these shocks on every endogenous variable is presented in Appendix 2.2.

3.2 Theory-Driven Sign Restrictions for the Pharmaceutical Sector

The imposed theory driven sign restrictions have been discussed in 2.2.2. In this section, we give further details as regard the application to the US pharmaceutical sector.

Recalling the identification of supply shocks, we argue that unemployment is the variable that allows us to distinguish a standard supply shock from unemployment-generating

[7] As concerns the pharmaceutical sector, panic-buying is a phenomenon that foresees induced demand for stocking medication by public due to the fear of s forthcoming shortage, i.e. price rise

[8] Around mid-March 2020, the Federal Reserve Bank cut its target interest rate near zero in an attempt to support the economy during the Covid-19 crisis. Additionally, it purchased $700 billion worth of Treasury bonds and mortgage-backed securities and it struck a deal with 5 central banks to lower the interest rates on currency swaps to have financial markets functioning in the usual way.

supply shocks. Specifically, we argue that a standard supply shock will decrease it, whereas unemployment-generating supply shocks will increase it in the short run. As it applies to Covid-19, such a restriction is imposed since it is reasonable to assume that during Covid-19 crisis many skilled and talented professionals needed to be employed in the pharmaceutical sector due to the high pressure it was experiencing to find a new vaccine. Moreover, many successful companies that were not involved in the pharmaceutical sector whatsoever, were also finding ingenious ways to be active players in this sector. For example, Fendi, the Italian luxury fashion house, as well as Gucci and Prada, started producing medical face masks when the global emergency arose. Nevertheless, as regards the vaccine, it is reasonable to say that at the end, there will be one big winner company and many losers and, accordingly, unemployment will rise again in this sector. In fact, at the end of this emergency, the pharmaceutical sector will have a lot of professionals employed and will need to downsize. Moreover, the non-pharmaceutical companies that are now trying to be active players in this sector, will have to return to their own business and, all the extra professionals they have hired to face the emergency, might not be needed anymore.

Moving on to demand-type shocks, some recent literature also shows that, especially in the pharmaceutical sector, investments and demand shocks are depicted by prices. This is the case since it is commonplace to assume that the more medicine research develops, the more people spends on drugs and medicaments. In fact, by looking at the Consumer Price Index of 1950 or 1960 compared to 2019 and 2020, it is blatant that people were spending much less on medicines in the past.
We also argue that in the first quarter of 2020, the investments shock positively affected the stock market of the pharmaceutical sector since significant investments were made in this sector. Accordingly, in the long run the amount of money invested in this sector is likely to decrease. Whereas, as regards the financial shock, it is possible to say that it had a negative impact on the stock market index in the first quarter of 2020. This is the case, since current patterns suggest that pharmaceutical companies are receiving a larger amount of money, which is likely to bring the index down, i.e. up again in the long run. These two shocks are standard shocks in the economy. In this model, the shock associated with the Covid-19 is only one, i.e. supply2. Nevertheless, this specific shock needs to be as much separately identified as possible. In fact, one could argue that investments in this sector do not necessarily increase following a health crisis but could increase also due to other factors. For example, during the 2000 "dot-com bubble" investments experienced a boom in every sector and, of course, also in the pharmaceutical sectors (Doms, 2004). Accordingly, the sign restrictions presented in Table 1 above ensure that it is accounted also for this factor and that the shock caused by Covid-19 in the pharmaceutical sector is not confused with other shocks.

3.3 Structural Analysis, Results, and Implications

In this section, we present the results derived from the estimation of the formerly identified model. First, the variance decomposition matrix will be discussed, which provides details on the relative position of each innovation in affecting each variable. Second, the historical decomposition will be presented to state the contribution of every structural shock to the forecast error at each point in time. Third, the different impulse response functions will be depicted to track the impact of a one-time shock to one of the structural errors on the present and future values of every endogenous variable. In an additional section some policy

implications of the results will be discussed.
Before digging into the results discussion, we provide a brief summary of the SVAR model identified in the previous sections. It includes 4 lags and is estimated on US quarterly data in levels from the second quarter of 2000 to the last quarter of 2020. The list of data series employed in this research is depicted in Table A.1 in A. Moreover, the model has 5 identified shocks, as summarized in Table A.2.

3.3.1 Variance Decomposition Analysis

The variance decomposition matrix separates the variation in each endogenous variable into the component shocks of the estimated SVAR model. Specifically, it tells what fraction of the variance of the forecast error in predicting $\mathbf{y}_{i,T+h}$ is due to the structural shock $\boldsymbol{\epsilon}_t$. Results presented in Table 3 are based on the median draw that satisfies the imposed sign restrictions. The portion of the variance of each endogenous variable attributable to each shock is described over three horizons, i.e. 1, 5, and 20.

The main result is that supply shocks, both Supply 1 and Supply 2, have played the most important role in explaining fluctuations in industrial production, producer prices, and the unemployment rate. In fact, it is possible to see that in the first horizon these two shocks accounted for approximately 70% of the variations in industrial production and producer prices, and for more than 90% of the variations in the unemployment rate.

To describe these results in deeper details, we do so from two perspectives, i.e. from the shocks and from the endogenous variables point of view.

To begin with the first one, Table 3 shows that the supply shocks, i.e. Supply 1 and Supply 2, are the main driver of the unemployment rate variability within the US pharmaceutical sector. In fact, they explain approximately 97% of the fluctuations in this variable. We notice that the relevance of Supply 1 shock slightly increases over time, as opposed to Supply 2 shock. that drops to 15% at horizon 20. The same applies to the industrial production, since we see that it is mostly explained by supply shocks at all horizons. As regard the demand shock, it is the main driver of variations in the investments in the US pharmaceutical sector: at horizon 1 it accounts for 26% of the fluctuations, whereas at horizon 20 it is estimated to fall to approximately 12%. Concerning the investment shock, Table 3 clearly shows that it is the largest driver of variations in the stock market index. In fact, it is estimated to drive 72% of the fluctuations. This share remains quite high also up until horizon 20, being expected to amount to 55%. Lastly, we observe that the financial shock together with the demand shock, is a big driver of the fluctuations in the investments in the US pharmaceutical sector since it accounts for 31% of the variations at horizon 1 and remains fairly solid over time. We can therefore conclude that investments in the US pharmaceutical sector are primarily driven by demand-shock types, including financial shocks. This is important to be underscored since the role played by financial shocks in describing the long-run dynamics of a macro-financial environment has been understood only recently and much work still needs to be done. Indeed, in most DSGE models, financial shocks were not considered and their relevance has been discussed only in recent studies, as introduced by Borio (2012).

At this point, we describe these results from the endogenous variables perspective. Table 3 shows that variations in the industrial production index and in the producer prices index are primarily explained by supply-shocks types. Indeed, demand shocks only account for approximately 30% of the variations, with the remaining 70% being attributable to supply shocks. At next horizons, we see, though, that the investment shock takes a more important

Table 3: Table showing the median forecast error variance decompositions over horizons 1, 5, and 20

Median Forecast Error Variance Decompositions for the Baseline Model						
	Horizon	Supply 1	Supply 2	Demand	Investment	Financial
Industrial Production Index	*1*	0.39	0.34	0.17	0.05	0.05
	5	0.55	0.27	0.13	0.03	0.02
	20	0.64	0.15	0.01	0.09	0.11
Producer Price Index	*1*	0.35	0.33	0.15	0.09	0.08
	5	0.21	0.28	0.08	0.33	0.10
	20	0.25	0.13	0.14	0.29	0.19
Investment	*1*	0.01	0.03	0.26	0.39	0.31
	5	0.10	0.26	0.05	0.30	0.29
	20	0.15	0.15	0.12	0.24	0.34
Unemployment Rate	*1*	0.60	0.37	0.01	0.01	0.01
	5	0.69	0.15	0.07	0.02	0.07
	20	0.67	0.15	0.08	0.03	0.07
Stock Market Index	*1*	0.01	0.01	0.05	0.72	0.21
	5	0.04	0.04	0.12	0.56	0.24
	20	0.04	0.04	0.13	0.55	0.24

role in explaining fluctuations in producer prices.
As regards the investments in the US pharmaceutical sector, Table 3 shows that the biggest driver of their variability were demand-shocks types. While the financial shock gains relevance over horizons, demand and investment gradually decrease theirs. It is also possible to see that the two supply shocks were the least important in explaining variations in the investments in the US pharmaceutical sector.
Moving on with the unemployment rate, Table 3 shows that supply shocks were by far the largest driver of fluctuations in this data series. In fact, nearly 97% of the variations can be attributed to these shocks. Investment, and Financial shocks play a minor role in explaining variations that can be considered negligible since close to 1%. These patterns are forecasted to hold in the future since even at horizon 20, supply shocks are still the major driver. It also remarkable to notice that the contribution of the investment shocks increases over time as well as the one of the financial shock.
Lastly, the largest driver of the stock market index's fluctuations was the investment shock. In fact, it explains 72% of the variability in this data series. The financial shock also plays a role in describing fluctuations at horizon 1, while the other three shocks are not important. As regards the forecasts, the situation changes a little. In fact, even if the investment shock still remains the major driver, the other shock gradually increase their importance over time, with the exception of the financial shock, the contribution of which slightly decreases.

As stated at the beginning of the section, these variance decompositions are based on the median draws satisfying the sign restrictions at each horizon. Literature is very controversial about how to best report evidence from the sign-identified SVAR model. Some authors, such as Inoue and Kilian (2013), argue that structural response functions should be calculated from the posterior mode of the joint distribution of admissible models both in the fully identified and in the partially identified case. Others, such as Fry and Pagan (2011), endorse the idea that to summarize the central tendency of the estimated response functions, average draws would do a better job. Just recently, another branch of authors raised its voice claiming that the whole distribution should, instead, be taken into account (Baumeister and Hamilton, 2019).

While we do not seek to enter this debate, we still made sure that our results were robust to approaches different than the median draws. Tables A.4 and A.5 in Appendix A show the average and the modal forecast error variance decompositions respectively for the baseline model.

To conclude, it is useful to summarize these results with a special focus on the unemployment-generating supply shock. So far, it has been proved that *(i)* it played an important role in explaining the major fluctuations in the US pharmaceutical macro-financial environment, and it was one of the main driver, *(ii)* it was considerably important for fluctuations in the industrial production index in the US pharmaceutical sector, and *(iii)* it was also important for fluctuations in the producer prices and unemployment rate in the US pharmaceutical sector, yet not the main responsible.

3.3.2 Historical Decomposition Analysis

To provide a glimpse about historical fluctuations of our baseline model through the lens of our identified shocks, we provide an historical decomposition.

Figure 1 shows the contribution of each identified shock to the total forecast error at each point in time from 2000 to 2020 for the Industrial Production Index.[9]

Supply shocks play a major role historically. Indeed, we can observe that they explained a big part of the fluctuations. Their relevance becomes higher in conjunction with the major epidemic events of the modern era. According to the WHO, these are the SARS of 2002/2003,[10] the H1N1 of 2009/2010,[11] also known as swine flu, and the Zika Virus of 2015/2016.[12] As a matter of fact, we can see that between 2002 and 2003, supply shocks have explained a large part of the variations in industrial production in the US pharmaceutical sector. The same applies to 2009/2010 and 2015/2016.

Figure A.10 in Appendix A shows the historical decomposition based on the unemployment rate. Similar conclusions can be drawn.

[9] The historical decomposition has been computed in two steps. First, the series of reduced form residuals has been converted into a structural residuals series. Second, the cumulative contributions of every structural component to the reduced form forecast error has been computed.

[10] Severe Acute Respiratory Syndrome. It is a virus that causes respiratory symptoms and was first identified in 2002 in China. It then spread worldwide, infecting more than 8 thousand people.

[11] Commonly referred to as the swine flu, it begins to spread in early 2009 in Mexico and the US. By June 2009 it has reached more than 70 countries worldwide and by the end of 2010, when WHO officially announces the pandemic's end, it has killed around 575,400 people worldwide.

[12] This virus is mainly transmitted by mosquitoes and starts to spread in Brazil in early 2015. By mid 2016, it reaches more than 60 countries worldwide including the US. The WHO announces the pandemic end's in November 2016.

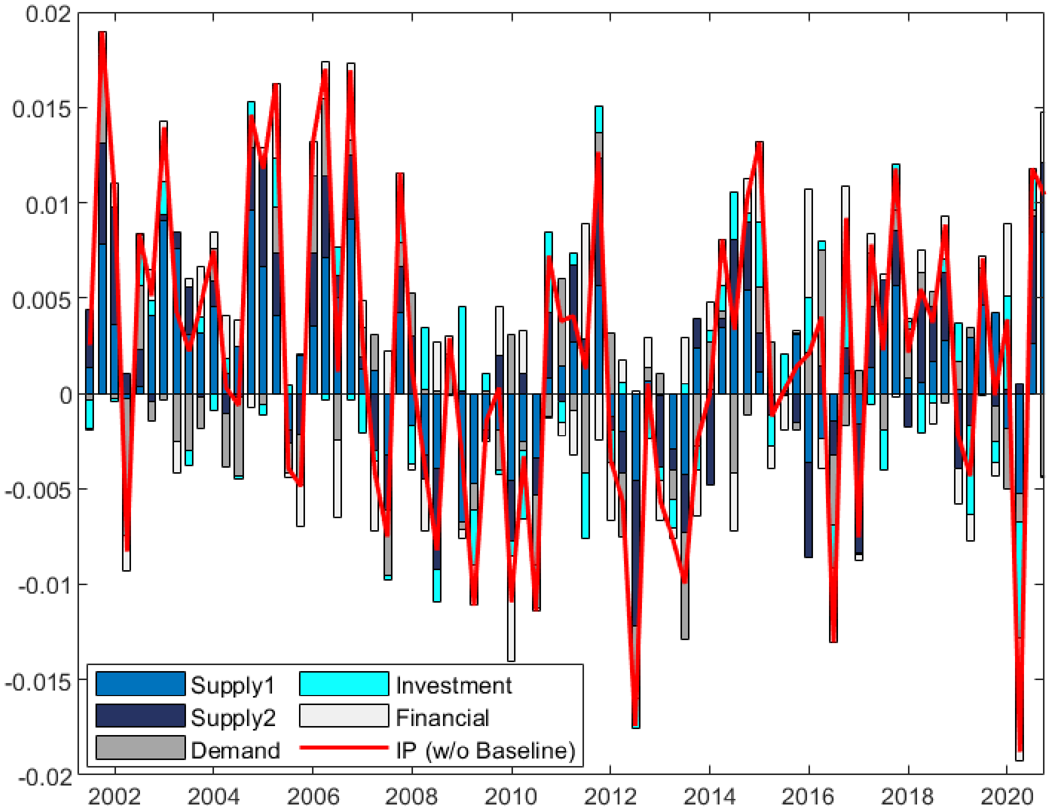


Figure 1: *Contribution of Shocks to Deviations in the Pharmaceutical Industrial Production Growth from its Baseline Forecast for the Period 2000-2020*

3.3.3 Impulse Response Functions

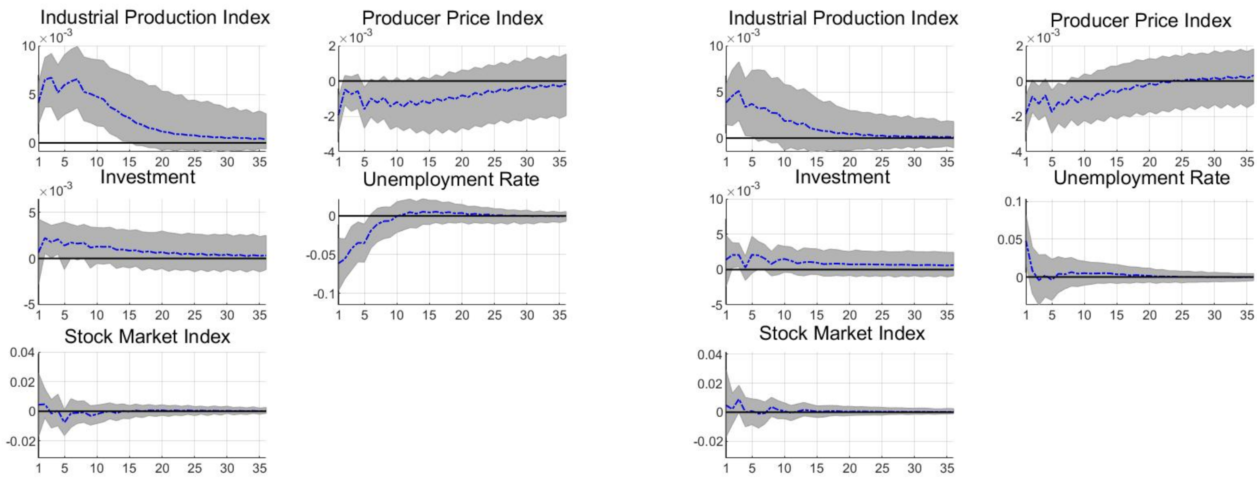
Impulse response functions are another important result of the model estimated in this research. In fact, they provide further details on the fluctuations that took place in the US pharmaceutical sector. Particularly, they outline the effect of a one-time shock to one of the structural errors on the present and future values of the endogenous variables included in the model. This is only possible when the error terms are uncorrelated, i.e. they are in their structural form. Impulse response functions are derived starting from Equation (3) as follows:

$$\mathbf{y}_t = \mathbf{F}\mathbf{y}_{t-1} + \mathbf{A}^{-1}\boldsymbol{\epsilon}_t \;\; IRF(0) = \mathbf{A}^{-1} \;\; IRF(1) = \mathbf{F}\mathbf{A}^{-1} \;\; IRF(2) = \mathbf{F}^2\mathbf{A}^{-1} \tag{6}$$

where the first equation recalls Equation (3), IRF stands for Impulse Response Function, and the 0, 1, 2 in brackets are the horizons at different points in time.
Figure 2 below displays the impulse response function of Supply 1 and Supply 2 shocks. The graphs in Figure 2 below confirms the importance of the unemployment-generating supply shock in explaining fluctuations in the US pharmaceutical sector and of supply shocks in general, confirming the results of the median variance decomposition discussed in 3.3.1.

We observe that Supply 1 and Supply 2 shock had a similar and major impact on the industrial production and on producer prices in the US pharmaceutical sector. Specifically,

Figure 2: *Impulse Responses for the Baseline Model to a One-standard-deviation Supply Shocks*
Note. *The blue dash-dotted lines render the posterior median at each horizon; the grey areas render the 68th posterior probability region of the estimated impulse responses.*



(a) *Supply 1 Shock* (b) *Supply 2 Shock*

they considerably increase the industrial production, while decreasing producer prices. The effect of Supply 1 and Supply 2 shock on the industrial production persists until horizon 15, when they fade away. Instead, as regards the short-run effects on producers prices a little distinction needs to be made. In fact, while both shocks brought prices down by the same amount at impact, at horizon 20 Supply 2 shock started to induce a positive effect that increased prices, albeit Supply 1 did not, with prices remaining negative.

Figure 2 clearly shows that unemployment is what uniquely distinguish a standard supply shock from a supply shock that, indeed, generate unemployment. As a matter of fact, we notice that while following a standard supply shock (panel 4 of Figure 2a) unemployment decreased in the US pharmaceutical company, it increase (panel 4 of Figure 2b) following a supply 2 shock. The patterns reverse quite quickly, though. After horizon 1, supply 2 shock gradually decrease unemployment, while Supply 1 shock increase it. In the short-run, the two results align. At horizon 10 the effect of a standard supply shock on unemployment loosens and the same happens for Supply 2 shock at horizon 5. This is an interesting result since it suggests that the need to produce, develop, and market a vaccine, for example against Covid-19, overcame the need to produce medicaments and drugs and that such need employed more and more people in the US pharmaceutical sector. This finding is line with the framework of this research since it is reasonable to assume that when Covid-19 hit the economy, every sectors had to face unemployment. Nevertheless, the pharmaceutical industry recovered after a few months since it was the main responsible for marketing and developing a new vaccine and, consequently, had to hire new talented workforce. Therefore, we conclude that the unemployment-generating supply shock was somehow positive for the pharmaceutical sector during COVID-19 since it attracted an increased number of workforce and contributed to reduce unemployment, which has been a severe issue for the US in the first months of 2020.

The response of investments and the stock market index is negligible since it is possible to observe that the blue dash-dotted line is very close to 0 at horizon 1. Accordingly, we conclude that these two variables are not the main drivers of fluctuations in the US pharmaceutical sector.

While the focus of this paper lies in the supply shocks, it is nevertheless interesting to analyze our model's forecasts for the other identified shocks. To do so, in Figure 3 we combine

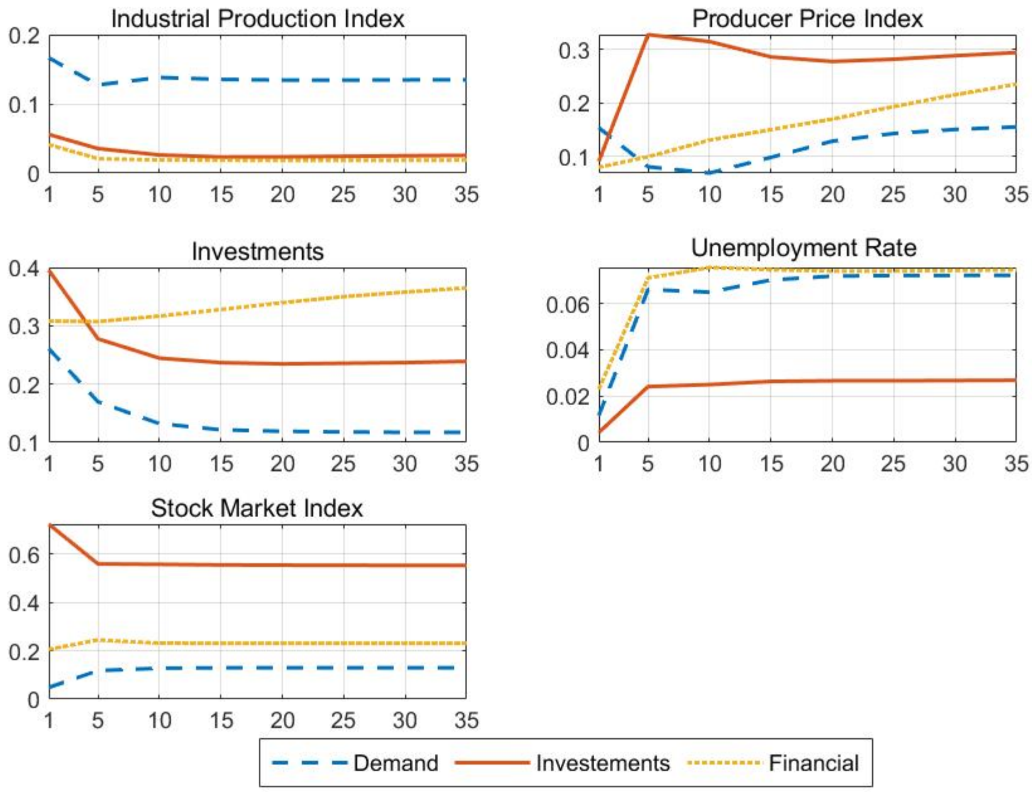


Figure 3: *: Median Impulse Responses for the Baseline Model to a One-standard-deviation Demand, Investment, and Financial Shock*

the median impulse responses of each variable to our demand-kind shocks in one single graph. Please refer to Figure A.6 in Appendix for the single impulse responses. We observe that demand shocks have protracted positive, i.e. negative effect on industrial production, and on investments and the stock market index, respectively. Their impact on the unemployment rate is negligible since numbers are very small and their impact on producer prices is difficult to comment on since there seem to be some seasonal effects in this series. From Figure 3, we see that the investment shock significantly increased producer prices, which is predicted to have a positive response for approximately 10 horizons. On the contrary, it decreased investments and stock market prices until horizon 5, which then holds steady. As regards industrial production and unemployment rate, its impact is negligible. Lastly, as regards the financial shock, it undoubtedly increased producer prices, investments, and stock market prices. Its impact on industrial production and unemployment rate is negligible since it follows a pattern that is very close to 0 for the whole period considered.

3.3.4 Robustness Checks

To confirm our results, we conducted a selection of robustness tests which we present in this section. Firstly, we modify our stock market index considering only the companies that contributed to the vaccine production in the US, i.e. Pfizer, Johnson and Johnson, and Moderna. Secondly, we impose that the unemployment-generating supply shock was the largest one on the last quarter of 2020, i.e. when the second big wave hit many countries worldwide. Lastly, we redid our analysis excluding the year of Covid-19, i.e. 2020 to check for applicability to ordinary times.

Robustness Check 1: Stock Market Index with Vaccine Producers Only As a first robustness check, we modified our stock market index considering only the companies that contributed to the vaccine production in the US. The new selection of companies considered along with their market capitalization and weight is shown in Table 4 below.

The median variance decomposition in Table 5 below shows that our results holds.

Table 4: *Table showing the companies for the first robustness check. Data were retrieved on May 13th, 2021.*

**billion f US$*	**Market Cap***	**weight**
Johnson & Johnson	$ 381.11	59%
Pfizer Inc.	$ 208.25	32%
Moderna	$ 57.57	9%

Indeed we are still seeing supply shocks as the bigger contributors to variations in industrial production and, most importantly, the unemployment rate, explaining together 70% of the fluctuations. Not surprisingly, we observe some major changes in the Stock Market Index and in the unemployment rate itself.

We can see that the financial and supply 2 shock assume a greater importance in explaining fluctuations in the stock market index. In fact, the former explained 44% of the variations, as opposed to 21% in the baseline case, while the latter explained 11.69% of fluctuations, compared to the 1% of the baseline case. These results holds in the short run since at horizon 5 and 10 these percentage remain approximately the same, slightly increasing for Supply 2 shock and remaining constant and then marginally decreasing for the financial shock. Moreover, we observe that Supply 1 shock takes on importance in the short run, since at horizon 20 it is predicted to explain 19% of the variations, compared to the 4% in the baseline case. These findings are in line with the very idea of this robustness check since it underlines the importance of the vaccine producers in explaining the fluctuations in the stock prices.

Interestingly, we discern that when considering only the vaccine-producer companies, the financial shock assumes a larger role in explaining variation in the unemployment rate. Indeed, it explains 20% of the variations, as opposed to 1% in the baseline case. Then, in the short-run, we see this percentage decreasing, reaching only 12% at horizon 20. This serves as a further confirmation that while at the beginning of an emergency, many workers were hired by the big pharmaceutical companies to produce a vaccine, when the task was accomplished many people had to be laid off to continue with the ordinary business.

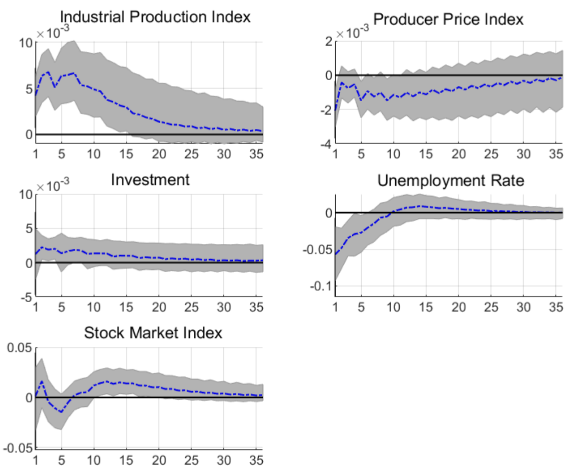
The analysis of the impulse response functions confirms these results. Figure 4 reports the median impulse response functions of the supply shocks, while all the other shocks, i.e. demand, investment, and financial are included in Figure 5. Please refer to Appendix A for all the other single impulse response function graphs.

Figure 4 highlights once again the importance of Supply 2 shock in explaining fluctuations

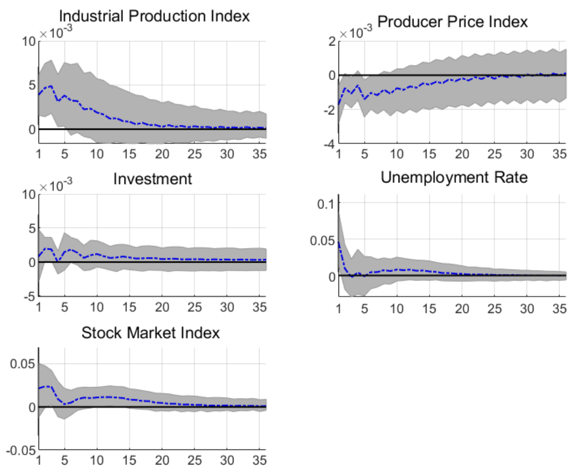
Table 5: *Table summarizing the median error forecast variance decompositions over horizons 1, 5, and 20.*

Median Forecast Error Variance Decompositions for Robustness Check 1 Model						
	Horizon	Supply 1	Supply 2	Demand	Investment	Financial
Industrial Production Index	*1*	0.39	0.33	0.19	0.04	0.05
	5	0.55	0.28	0.12	0.04	0.01
	20	0.64	0.19	0.10	0.06	0.01
Producer Price Index	*1*	0.37	0.26	0.17	0.09	0.11
	5	0.21	0.28	0.08	0.33	0.10
	20	0.24	0.18	0.13	0.28	0.17
Investment	*1*	0.02	0.02	0.31	0.35	0.30
	5	0.13	0.08	0.22	0.32	0.25
	20	0.17	0.10	0.15	0.33	0.25
Unemployment Rate	*1*	0.43	0.28	0.01	0.08	0.20
	5	0.48	0.13	0.02	0.23	0.14
	20	0.48	0.14	0.04	0.22	0.12
Stock Market Index	*1*	0.00	0.12	0.07	0.37	0.44
	5	0.06	0.18	0.08	0.24	0.44
	20	0.19	0.22	0.07	0.20	0.32

Figure 4: *Impulse Responses for the Robustness 1 Model to an One-standard-deviation Supply Shocks*
Note. *The blue dash-dotted lines render the posterior median at each horizon; the grey areas render the 68th posterior probability region of the estimated impulse responses.*



(a) *Supply 1 Shock*



(b) *Supply 2 Shock*

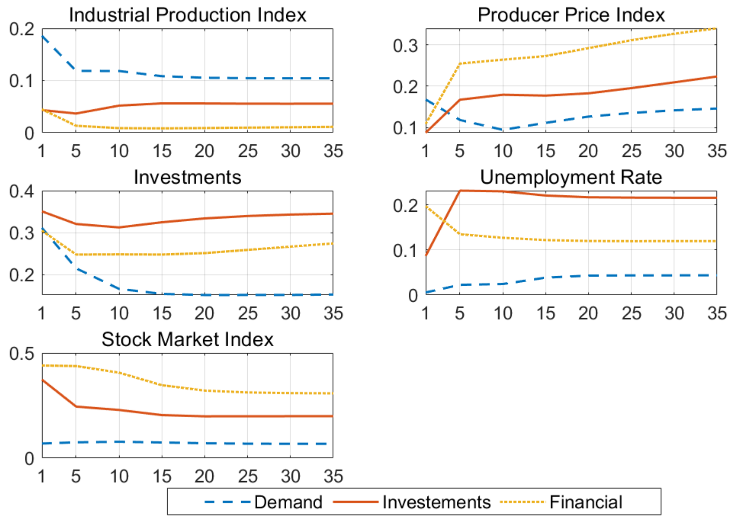


Figure 5: *Median Impulse Responses for the Robustness 1 Model to a One-standard-deviation Demand, Investment, and Financial Shock*

in the stock market index. We observe that it discernibly bring them up. According to the model's forecasts, this should hold in the short run at a decreased magnitude since we see the posterior median draw slowly approaching zero. Supply 1 also assumes an increased importance, as discussed above. Looking at the fifth panel in Figure 5, the importance of the financial shock for the stock market index is clear. In fact, we observe that it significantly increase stock prices and it holds until horizon 35.
The fourth panel of Figure 3 shows, as discussed above, that the financial shock has also a major role in explaining unemployment.

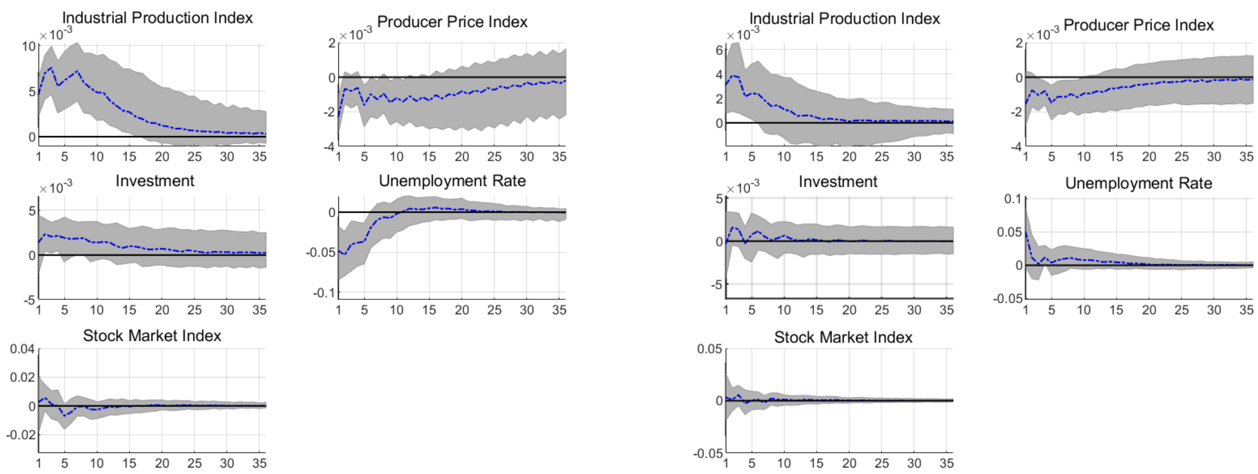
Robustness Check 2: Narrative Restrictions - Shock on the Fourth Quarter of 2020 As a second robustness check, we applied narrative restrictions imposing the supply shock triggered by Covid-19 on the last quarter of 2020 to check for major differences between the first and the second wave. In fact,it is known that during the last months of 2020 a second big wave hit many countries worldwide, with a negligible different timing.
As expected, the median variance decomposition in Table 6 below does not distance much from the baseline case. Indeed, we are still seeing supply shocks as the most important drivers of unemployment rate and industrial production. This is in line with our argument, since, as explained in previous sections, we believe that every wave of Covid-19 displays recurring features and that, therefore, can be analyzed with the very same framework, i.e the SVAR modeling we proposed. Some minor differences, though, can be outlined in the Investments. We can see that in the short run the Supply 2 shock looses on importance in explaining fluctuations in this variables with Supply 1 shock gaining on relevance. If during the first wave, the Supply 2 shock accounted on average for 15% of the variations in Investment, during the second wave, this percentage dramatically drops to approximately 4%. The interpretation of this trend could be that investments in the US pharmaceutical did not increase from January to December 2020 since governments and privates gave their contribution right at the beginning of the Covid-19 crisis and throughout the year such funds were employed to face the situation.

Looking at the impulse response functions, similar conclusions can be drawn. Figure 6

Table 6: *Table showing the median forecast error variance decompositions over horizons 1, 5, and 20*

Median Forecast Error Variance Decompositions for Robustness Check 2 Model						
	Horizon	Supply 1	Supply 2	Demand	Investment	Financial
Industrial Production Index	*1*	0.50	0.23	0.15	0.06	0.06
	5	0.54	0.28	0.13	0.0356	0.0259
	20	0.72	0.10	0.12	0.03	0.03
Producer Price Index	*1*	0.49	0.22	0.13	0.11	0.05
	5	0.29	0.21	0.08	0.31	0.11
	20	0.29	0.17	0.10	0.24	0.20
Investment	*1*	0.03	0.01	0.22	0.38	0.36
	5	0.17	0.04	0.15	0.29	0.35
	20	0.20	0.03	0.10	0.27	0.40
Unemployment Rate	*1*	0.42	0.48	0.03	0.00	0.07
	5	0.59	0.18	0.10	0.04	0.09
	20	0.57	0.19	0.11	0.04	0.09
Stock Market Index	*1*	0.00	0.01	0.03	0.77	0.19
	5	0.03	0.02	0.13	0.60	0.22
	20	0.05	0.02	0.14	0.58	0.21

Figure 6: *Impulse Responses for the Robustness 2 Model to an One-standard-deviation Supply Shocks*
Note. *The blue dash-dotted lines render the posterior median at each horizon; the grey areas render the 68th posterior probability region of the estimated impulse responses.*



(a) *Supply 1 Shock* (b) *Supply 2 Shock*

displays the impulse response of the Supply 1 and Supply 2 shock to all the endogenous variables, and 7 shows the median impulse responses for the other shocks. Please refer to

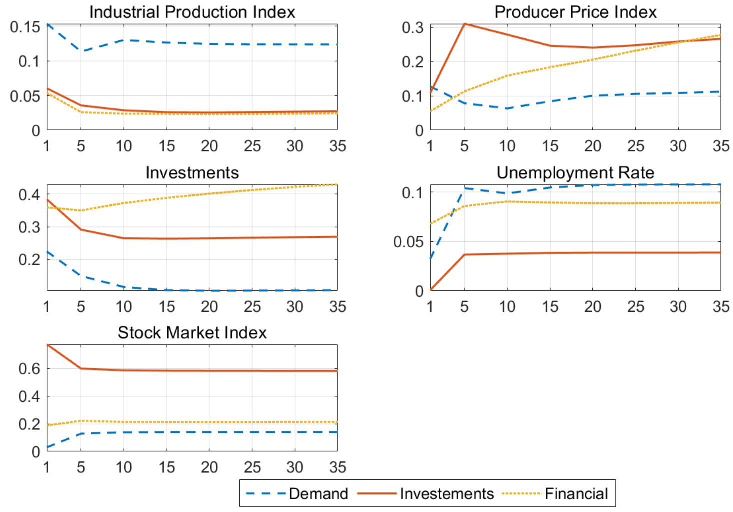


Figure 7: *Median Impulse Responses for the Robustness 2 Model to a One-standard-deviation Demand, Investment, and Financial Shock*

Figure A.8 in Appendix A for the other single impulse response functions.
Looking at the second panel of Figure 6, we can see that the Supply 2 shock had a very modest impact on the investments if compared to the baseline case. It brought investments up by a little, which then approaches 0 until horizon 20. Similarly, Supply 1 shock also gained on importance in explaining variations in the investments. Indeed, we can see that it brought investments up as of horizon 15, which then slightly decrease until horizon 20.

Robustness Check 3: Ordinary Times As a last robustness check, we excluded the year of the Covid-19 crisis, i.e. 2020, to see if our model holds for pre-COVID sample as well.

From Table 7 below, we can see that the importance of the Supply 2 shock has significantly shrunk for nearly every variable, which is mostly observable in the short-run. We detect the largest reductions as regards the industrial production and the investments. Indeed, if for the baseline case at horizon 5 and 20 the supply 2 shock explains 26% and 15% of variations in investments, for this robustness check it explains only 6% and 4%, respectively. This is reasonable since the need to develop new vaccines and treatments is less strong in ordinary times, but it still exists. In fact, our data set includes three other big pandemics, i.e. H7N1 of 2002, the SARS of 2003, and swine flu of 2009, among others.

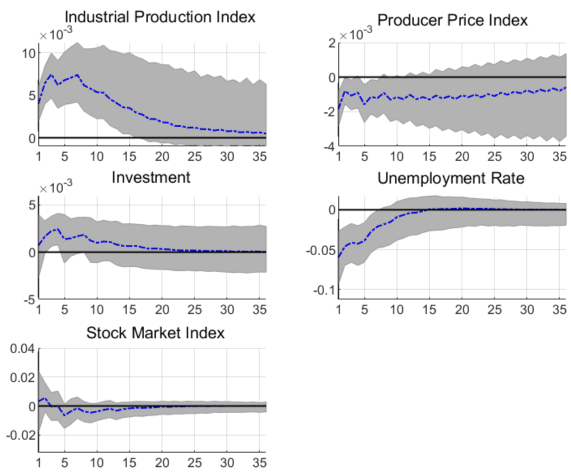
The impulse response function of Supply2 in Figure 8 shock confirms what has been stated above, i.e. that its impact shrinked and no major changes are observed. Figure 8 displays the impulse response of the Supply 1 and Supply 2 shock to all the endogenous variables, and Figure 9 shows the median impulse responses for the other shocks. Please refer to Figure A.9 in Appendix A for the other single impulse response functions.

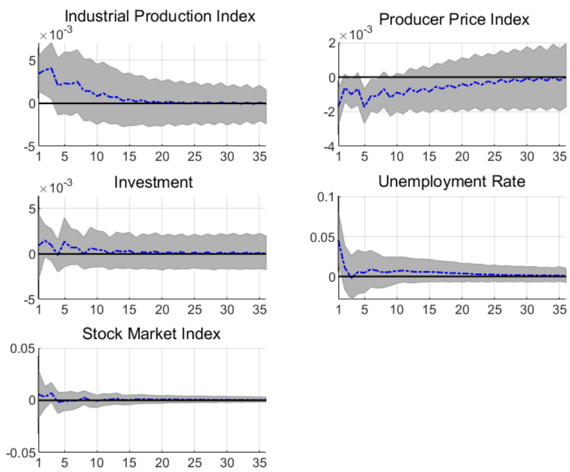
Looking at Figure 8 we can see that the contribution of the supply 2 shock is very tiny, especially as regards investments and the stock prices, since the posterior median draw is constantly around zero. We observe that the biggest impact of the supply 2 shock remains on the industrial production, producer prices, and the unemployment rate, with behaviors similar to trends described in the previous sections.

Table 7: *Table showing the median forecast error variance decompositions over horizons 1, 5, and 20*

Median Forecast Error Variance Decompositions for Robustness Check 3 Model						
	Horizon	Supply 1	Supply 2	Demand	Investment	Financial
Industrial Production Index	*1*	0.42	0.31	0.18	0.05	0.04
	5	0.65	0.17	0.10	0.06	0.02
	20	0.76	0.10	0.09	0.04	0.01
Producer Price Index	*1*	0.34	0.29	0.17	0.11	0.09
	5	0.29	0.26	0.08	0.26	0.11
	20	0.28	0.17	0.11	0.21	0.23
Investment	*1*	0.01	0.02	0.25	0.40	0.32
	5	0.15	0.06	0.16	0.29	0.34
	20	0.15	0.04	0.14	0.28	0.39
Unemployment Rate	*1*	0.58	0.34	0.00	0.01	0.07
	5	0.73	0.15	0.01	0.07	0.04
	20	0.73	0.16	0.01	0.06	0.04
Stock Market Index	*1*	0.00	0.02	0.05	0.71	0.22
	5	0.03	0.03	0.10	0.58	0.26
	20	0.06	0.04	0.11	0.54	0.25

Figure 8: *Impulse Responses for the Robustness 3 Model to an One-standard-deviation Supply Shocks*
Note. *The blue dash-dotted lines render the posterior median at each horizon; the grey areas render the 68th posterior probability region of the estimated impulse responses.*





(a) *Supply 1 Shock* (b) *Supply 2 Shock*

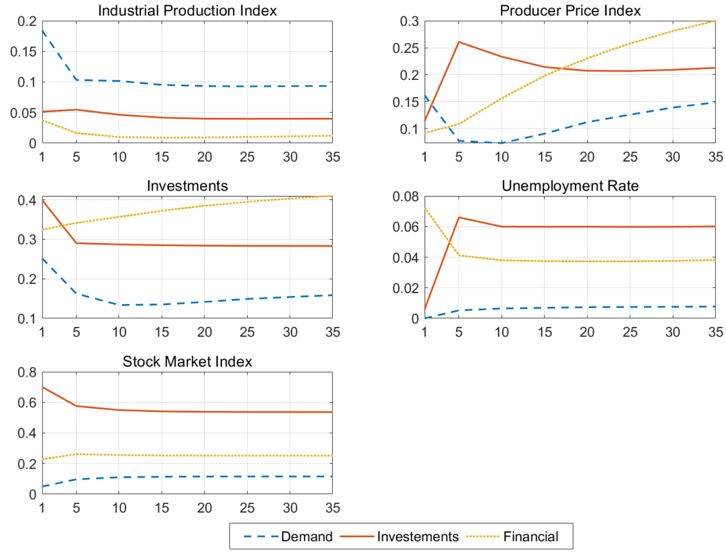


Figure 9: *Median Impulse Responses for the Robustness 3 Model to a One-standard-deviation Demand, Investment, and Financial Shock*

3.3.5 Policy Implications Results

To conclude, it is worthwhile to underscore why our research is relevant from an economic and financial point of view, and which implications can be drawn from the aforementioned results.

The research question we developed aims at analyzing unemployment-generating supply shocks in a macro-financial setting.

Economically, our work is relevant in that it offers informed opinions as to which macroeconomic variables matter the most in an industry that is seeing unemployment increasing following a supply shocks. When such event occurs, new hirings should be closely monitored since these could turn into terminations once the supply is not triggered anymore.

As regards the stock prices, our work offers insightful claims as to what drives stock prices. Looking at the whole corporate panorama, stock prices are primarily driven by investment and financial shock. Under extraordinary circumstances, considering only those companies that provide the greatest contribution, unemployment-generating supply shocks are among the biggest drivers of fluctuations in stock market prices. It follow that while investment and financial shocks are important drivers of stock market prices, supply shocks can be as well, if extraordinary times are being lived.

4 Conclusions

The aim of this paper is to assess the relevance of shocks originating in the US pharmaceutical sector to explain business-cycle fluctuations in a sign-restricted VAR.

Starting from a pool of variables depicting the US pharmaceutical sector, we estimate a SVAR model with the aim to quantify impulse responses to the economic shock in the US pharmaceutical industry. We identified the aforementioned model through a minimum set of sign restrictions dictated by economic theory and recent market developments. We study the

unemployment-generating supply shock along with standard supply, demand, financial, and investment shocks to best assess its impact on the macro-financial environment of the US pharmaceutical sector. In fact, the endogenous variables included in the model are industrial production, producer prices, investments, the unemployment rate, and stock prices. Accordingly, a structural analysis has been proposed to examine the results. The main results of the variance decomposition analysis are that the unemployment-generating supply played an important role in explaining the major fluctuations in the US pharmaceutical macro-financial environment. Particularly, it was considerably important in explaining fluctuations in industrial production, producer prices, and the unemployment rate. We deepened these findings analyzing the impulse response functions of each variable to all the five shocks included in the model. From this analysis it emerges that the unemployment-generating supply increase industrial production and decrease both producer prices and the unemployment rate. According to the model's predictions, this result should hold in the long run, with the only exception of the unemployment rate, which should decrease in the short run. Having stated this, it is also relevant to stress that the framework introduced in this paper could be employed to analyze future crises triggered by new pandemics or other waves of Covid-19.
In light of these conclusions, we have identified three different avenues for future research. First, the model presented in this research could be re-estimated identifying a non-linear SVAR that better captures the development over time of the economic shocks. In fact, it is reasonable to assume that a single shock, the unemployment-generating supply in this case, follows several patterns over time and is not linear. Second, it is important to further investigate a crucial link between healthcare crises and the role of governments: public funding. In fact, if we clearly showed the importance of the private sector with the stock market index we built, it would be interesting to understand how much public funding these companies actually received. Lastly, we stress that we concentrated on the US pharmaceutical sector only. Our results do not necessarily apply to countries that could be different in terms of industrial production, producer prices, and pharmaceutical-sector structure. Accordingly, it would be interesting to re-run the analysis focusing on other strong economies, such as Europe or China.

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A Appendix

Table A.1: Table summarizing the data series used for this research along with their sources

Data and Sources		
Variable	*Description*	*Source*
Industrial Production Index	Industrial Production in the Pharmaceutical and Nondurable Goods	FRED
Producer Price Index	Producer Price Index for the Pharmaceutical and Medicine Manufacturing Industry	FRED
Investments	Private Fixed Nonresidential Investments in the Pharmaceutical Industry	FRED
Unemployment Rate Rate	Unemployment Rate of Experienced Private Wage and Salary Workers in the Pharmaceutical Sector	US BLS
Stock Market Index Index	Stock Price of the best-performing US Pharmaceutical Companies	Yahoo Finance and own calculations

Table A.2: Table providing a brief description of the economic shock considered

Shocks			
	Description	*Type*	*Category*
Supply 1	Need to produce more medicaments and drugs	expansionary	supply
Supply 2	Need to develop and market vaccines for pandemic events	expansionary	
Demand	Prescription medicines shortage,i.e. increased hospitalization and demand for ventilators	expansionary	demand
Investment	Shock to the supply of capital	expansionary	
Financial	Shock to the demand for capital	expansionary	

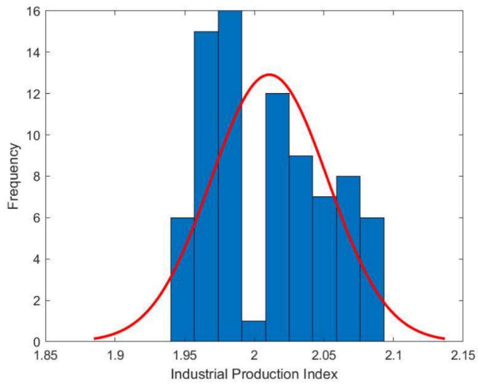
Table A.3: *Table describing the selection of companies included in the Stock Market Index*

Companies included in the Stock Market Index					
Company	*Description*	*Revenues*	*TA*	*TE*	*Nr Employees*
Johnson & Johnson	American multinational corporation developing medical devices, pharmaceutical and consumer packaged goods	$ 82.06	$ 157.73	$ 59.47	132,200
Pfizer Inc.	NYC based multinational corporation producing and developing medicines and vaccines for a wide range of medical disciplines	$ 51.75	$ 167.49	$ 63.14	88,300
Merck & Co., Inc.	New Jersey incorporated multinational company researching new medicaments and producing a wide range of legacy products	$ 42.29	$ 82.64	$ 26.70	69,000
Abbot Laboratories	Abbott Park (IL) based multinational company selling diagnostics, branded generic medicines and boasting a specific research unit	$ 31.90	$ 67.89	$ 31.30	107,000
Eli Elly & Co.	Indiana based pharmaceutical company active in vaccine research and drugs development	$ 24.56	$ 43.91	$ 10.91	33,815
Bristol-Myers Squibb Company	NYC based pharmaceutical company manufacturing prescription pharmaceuticals and biologics in several therapeutical areas	$ 26.10	$ 34.99	$ 14.13	23,300
Gilead Sciences, Inc.	Foster City (CA) based biopharmaceutical company researching, developing, and commercializing drugs	$ 22.45	$ 61.63	$ 22.65	11,800
Stryker Corporation	Kalamazoo (MI) based medical technologies firm producing implants, surgical equipment, and medical devices	$ 12.44	$ 30.17	$ 12.81	33,000
Regeneron Pharmaceutical Inc.	NYS based biotechnology company focused on neurotrophic factors and receptors	$ 7.86	$ 5.60	$ 3.65	8,100
Biogen Inc.	Cambridge (MA) based multinational biotechnology company specialized in the discovery and developments of medical treatments	$ 12.27	$ 23.65	$ 12.61	7,300
Moderna, Inc.	Cambridge (MA) based pharmaceutical and biotechnology company specialized in vaccines technologies based on mRNA.	$ 2.70	$ 7.34	$ 2.56	830

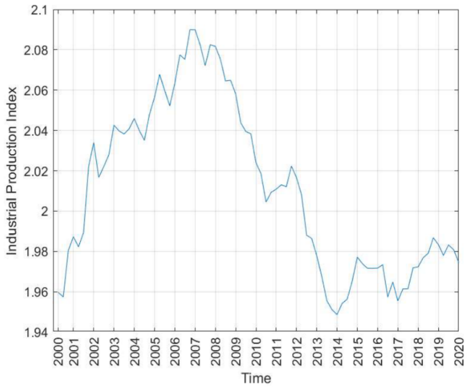
Figure A.1: *Industrial Production Index Series*

Summary Statistics	
Mean	2.0108
Median	2.0101
Standard Deviation	4.17%
Skewness	0.2818
Kurtosis	1.7694

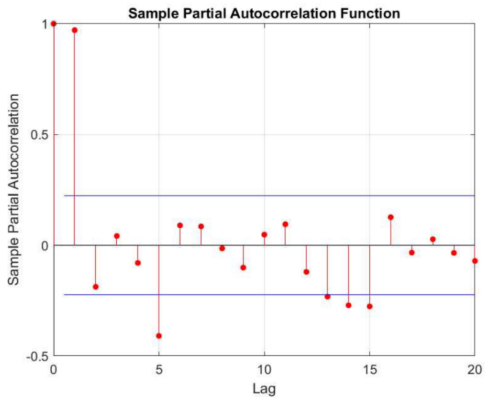
(a) Summary Statistics



(b) Histogram with the red curve representing the Gaussian curve



(c) Line plot

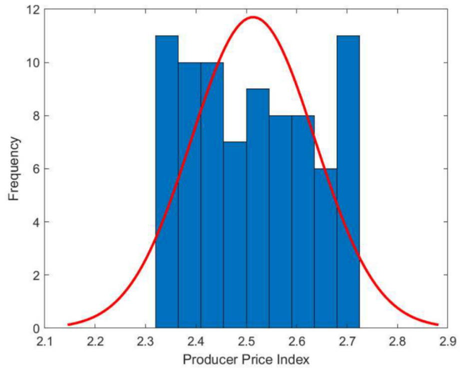


(d) Partial Autocorrelation Function

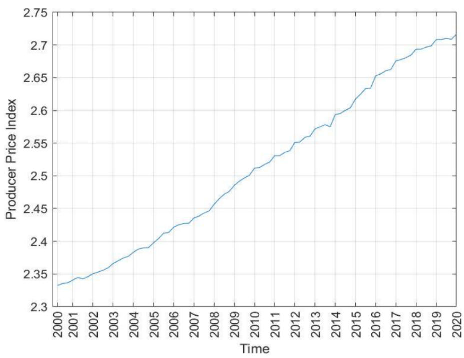
Figure A.2: *Producer Price Index Series*

Summary Statistics	
Mean	2.5135
Median	2.5122
Standard Deviation	12.20%
Skewness	0.1420
Kurtosis	1.7058

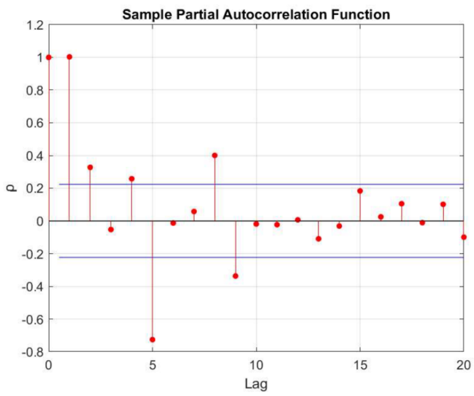
(a) Summary Statistics



(b) Histogram with the red curve representing the Gaussian curve



(c) Line plot

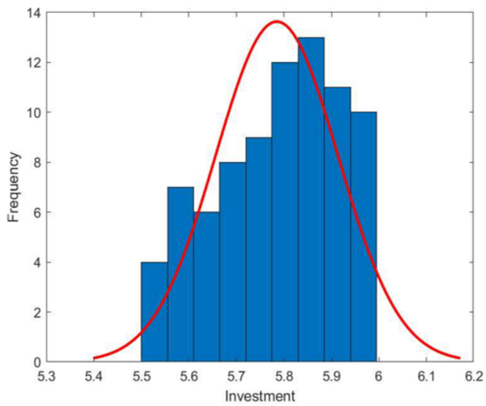


(d) Partial Autocorrelation Function

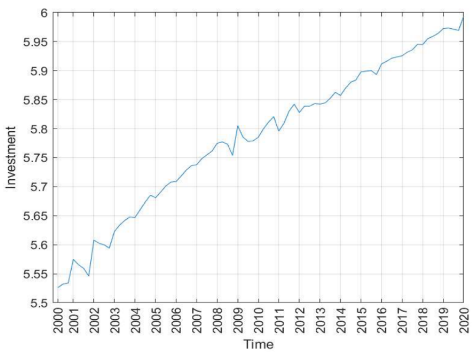
Figure A.3: Investments Series

Summary Statistics	
Mean	5.7850
Median	5.7977
Standard Deviation	12.79%
Skewness	-0.3272
Kurtosis	2.0989

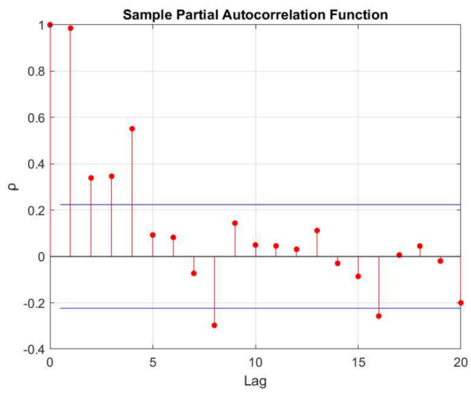
(a) Summary Statistics



(b) Histogram with the red curve representing the Gaussian curve



(c) Line plot

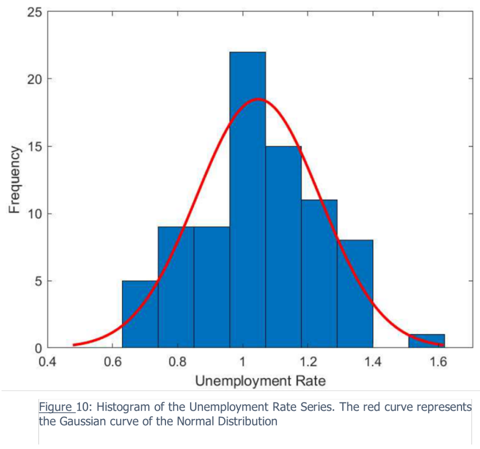


(d) Partial Autocorrelation Function

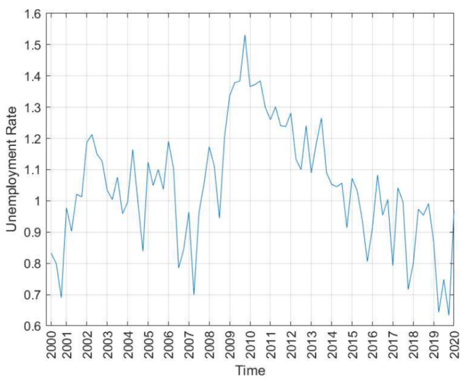
Figure A.4: *Unemployment Rate Series*

Summary Statistics	
Mean	1.0477
Median	1.0434
Standard Deviation	18.87%
Skewness	0.0165
Kurtosis	2.7542

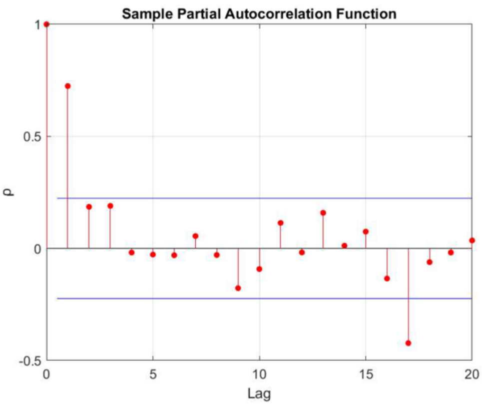
(a) Summary Statistics



(b) Histogram with the red curve representing the Gaussian curve



(c) Line plot

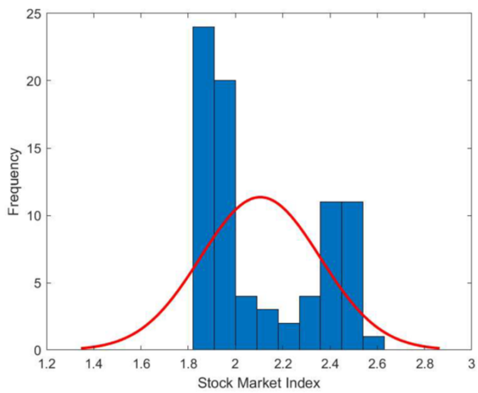


(d) Partial Autocorrelation Function

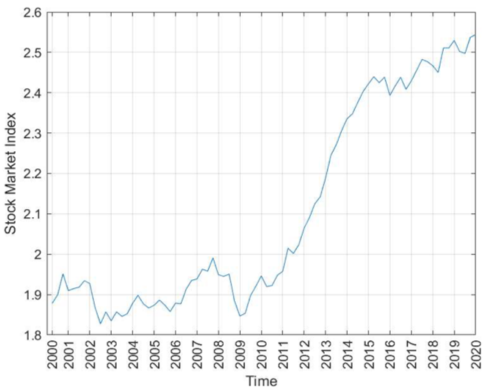
Figure A.5: *Stock Market Index Series*

Summary Statistics	
Mean	2.1050
Median	1.9544
Standard Deviation	25.13%
Skewness	0.5541
Kurtosis	1.5730

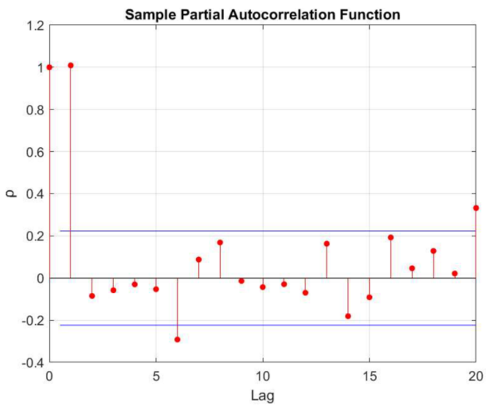
(a) Summary Statistics



(b) Histogram with the red curve representing the Gaussian curve



(c) Line plot



(d) Partial Autocorrelation Function

Table A.4: *Table showing the average forecast error variance decompositions over horizons 1, 5, and 20*

Note. This approach follows the idea of Fry and Pagan (2011)

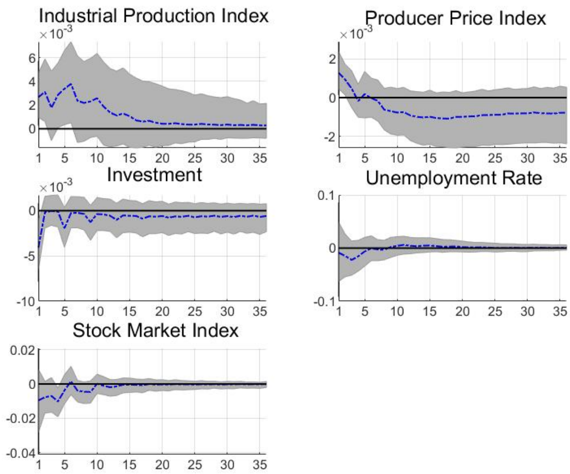
Average Forecast Error Variance Decompositions for the Baseline Model						
	Horizon	Supply 1	Supply 2	Demand	Investment	Financial
Industrial Production Index	*1*	0.06	0.69	0.15	0.06	0.04
	5	0.27	0.44	0.19	0.06	0.04
	20	0.24	0.32	0.34	0.07	0.03
Producer Price Index	*1*	0.49	0.28	0.10	0.02	0.11
	5	0.21	0.27	0.06	0.38	0.08
	20	0.07	0.25	0.14	0.30	0.24
Investment	*1*	0.00	0.00	0.25	0.61	0.14
	5	0.13	0.13	0.14	0.36	0.30
	20	0.11	0.14	0.10	0.35	0.30
Unemployment Rate	*1*	0.51	0.25	0.13	0.11	0.00
	5	0.51	0.17	0.13	0.09	0.10
	20	0.48	0.20	0.15	0.08	0.09
Stock Market Index	*1*	0.08	0.06	0.11	0.29	0.46
	5	0.06	0.18	0.13	0.26	0.37
	20	0.08	0.18	0.13	0.29	0.32

Table A.5: *Table showing the modal forecast error variance decompositions over horizons 1, 5, and 20*

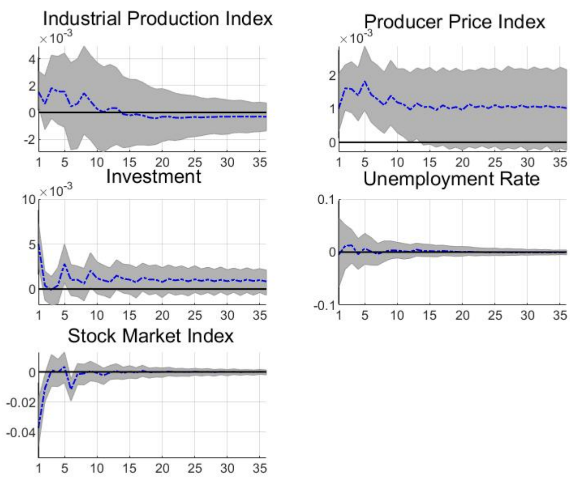
Note. This approach follows the idea of Inoue and Kilian (2013)

Modal Forecast Error Variance Decompositions for the Baseline Model						
	Horizon	Supply 1	Supply 2	Demand	Investment	Financial
Industrial Production Index	*1*	0.38	0.32	0.29	0.00	0.01
	5	0.56	0.22	0.15	0.05	0.02
	20	0.55	0.13	0.06	0.17	0.09
Producer Price Index	*1*	0.24	0.12	0.09	0.51	0.04
	5	0.18	0.03	0.04	0.72	0.03
	20	0.45	0.12	0.04	0.37	0.02
Investment	*1*	0.25	0.48	0.10	0.09	0.08
	5	0.23	0.53	0.09	0.06	0.09
	20	0.15	0.59	0.05	0.14	0.07
Unemployment Rate	*1*	0.54	0.02	0.11	0.05	0.28
	5	0.51	0.05	0.07	0.05	0.32
	20	0.46	0.06	0.08	0.08	0.32
Stock Market Index	*1*	0.09	0.00	0.00	0.60	0.31
	5	0.16	0.02	0.10	0.49	0.23
	20	0.17	0.04	0.13	0.43	0.23

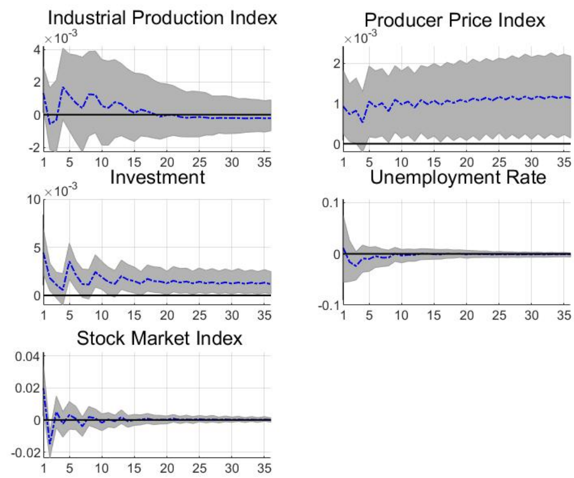
Figure A.6: *Impulse Responses for the Baseline Model to a One-standard-deviation Demand-Kind Shocks*
Note. *The blue dash-dotted lines render the posterior median at each horizon; the grey areas render the 68th posterior probability region of the estimated impulse responses.*



(a) *Demand Shock*

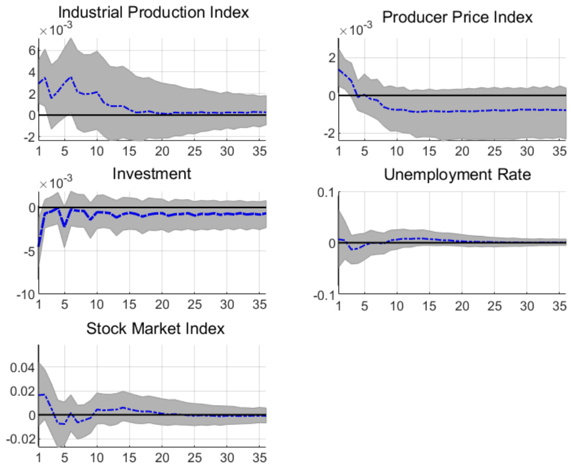


(b) *Investment Shock*

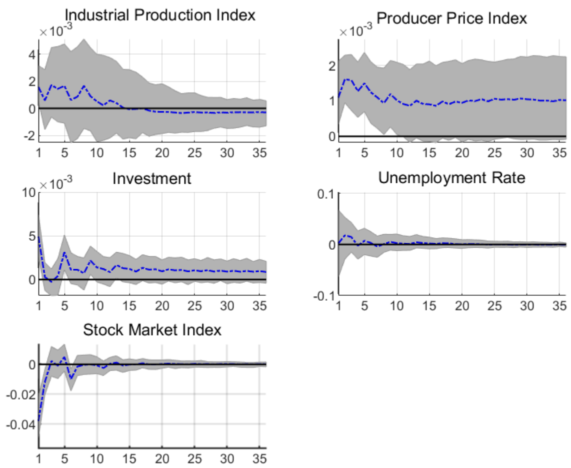


(c) *Financial Shock*

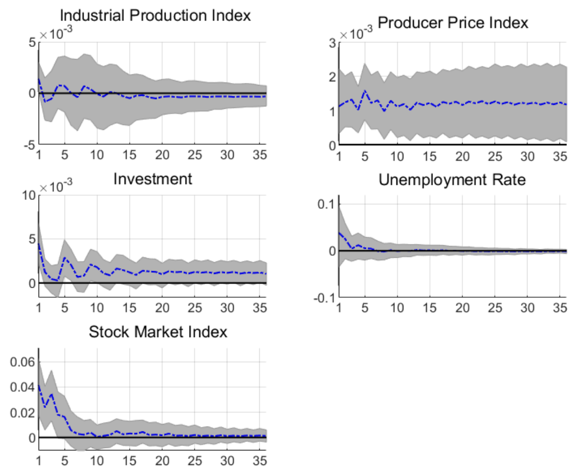
Figure A.7: *Impulse Responses for the Robustness Check 1 Model to a One-standard-deviation Demand-Kind Shocks*
Note. *The blue dash-dotted lines render the posterior median at each horizon; the grey areas render the 68th posterior probability region of the estimated impulse responses.*



(a) *Demand Shock*

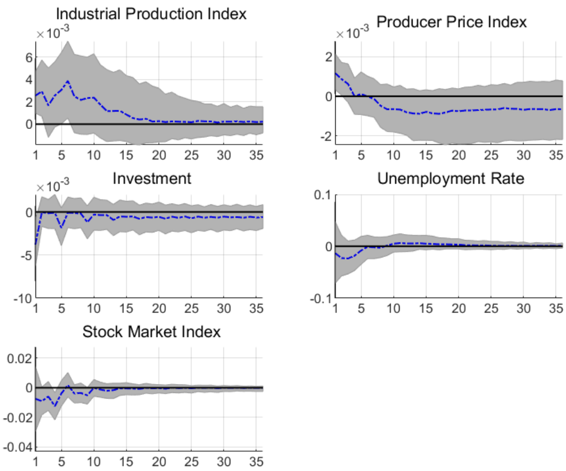


(b) *Investment Shock*

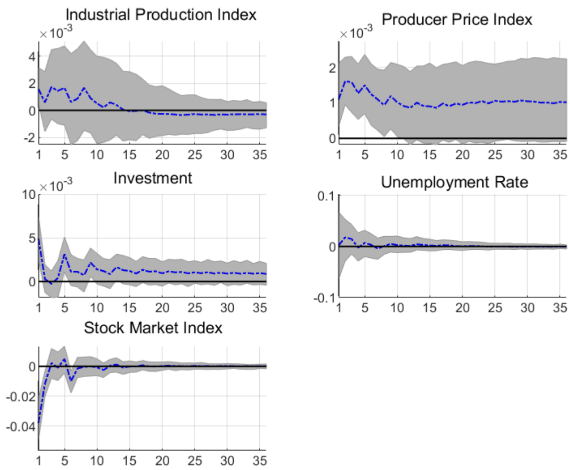


(c) *Financial Shock*

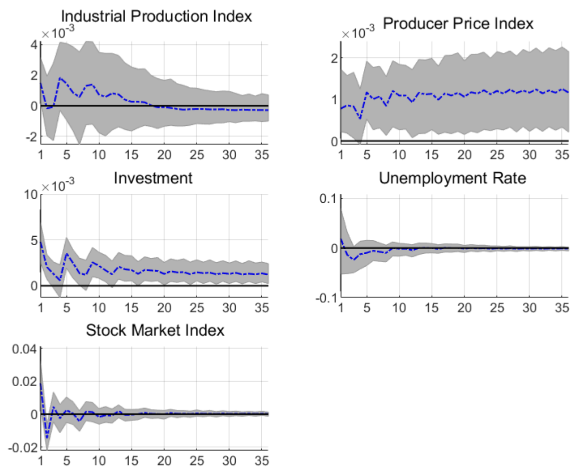
Figure A.8: *Impulse Responses for the Robustness Check 2 Model to a One-standard-deviation Demand-Kind Shocks*
Note. *The blue dash-dotted lines render the posterior median at each horizon; the grey areas render the 68th posterior probability region of the estimated impulse responses.*



(a) *Demand Shock*



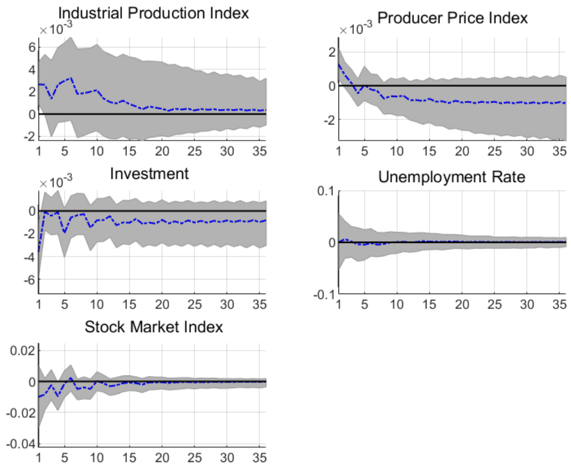
(b) *Investment Shock*



(c) *Financial Shock*

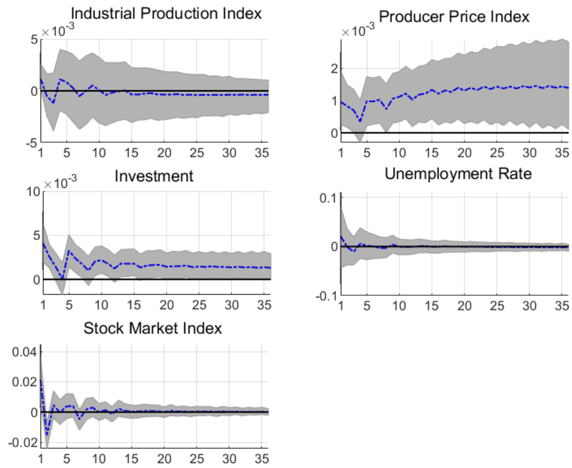
Figure A.9: *Impulse Responses for the Robustness Check 3 Model to a One-standard-deviation Demand-Kind Shocks*

Note. *The blue dash-dotted lines render the posterior median at each horizon; the grey areas render the 68th posterior probability region of the estimated impulse responses.*



(a) *Demand Shock*

(b) *Investment Shock*



(c) *Financial Shock*

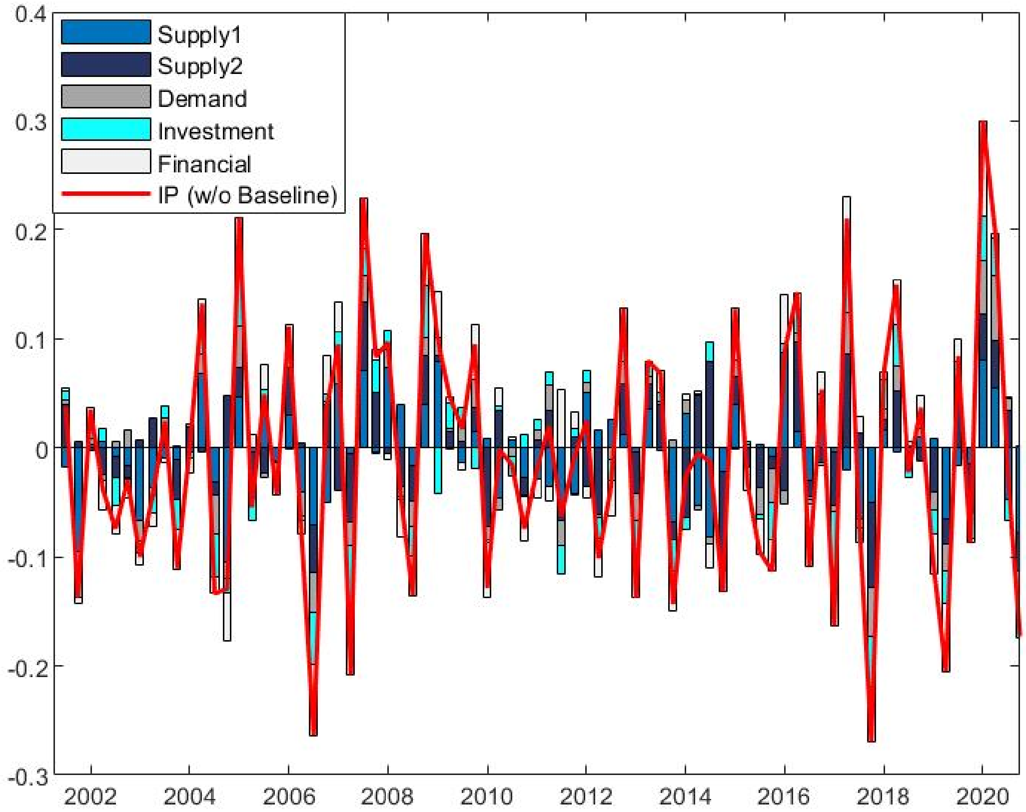


Figure A.10: *Contribution of Shocks to Deviations in the Unemployment Rate from its Baseline Forecast for the Period 2000-2020*