The Effects of Global Supply Chain Pressure on Sentiment, Expectation, and Uncertainty: A VAR Approach

Los efectos de la presión de la cadena de suministro global sobre el sentimiento, las expectativas y la incertidumbre: un enfoque VAR

Héctor Romero-Ramírez

Federal Reserve Bank of San Francisco, USA

Received: July 7, 2024.
Approved: October 29, 2024.

Abstract

This paper studies the relationship of global supply chain pressure with consumer sentiment, inflation expectation, and monetary policy uncertainty in the United States. A sample from January 1998 to January 2024 is used, and this paper uses a Vector Autoregression (VAR) approach based on the method proposed by Toda and Yamamoto (1995). The Granger causality test suggests that the predictions of inflation expectation based on its own past values and the past values of the global supply chain pressure are better predictions of inflation expectation than just using the past observations of inflation expectation. In contrast, Impulse Response Functions suggest that surprise increases in global supply chain pressure lead to increased inflation expectation and monetary policy uncertainty; this shock lasts up to two years. Meanwhile, the Impulse Response Functions suggest that surprise increases in the global supply chain pressure decrease consumer sentiment (confidence), lasting up to two and a half years. Afterward, the impact converges back to zero. Additionally, the Variance Decomposition results suggest that by the final period, the impulses of the global supply chain pressure explain over 22%, 7%, and 44% of the variation of consumer sentiment, monetary policy uncertainty, and inflation expectation, respectively.

Keywords: *Consumer, inflationary expectations, uncertainty, macroeconometric methods.*
JEL Classification: *E210, E310, D800, C500.*

Resumen

Este trabajo estudia el vínculo entre la presión de la cadena de suministro global y el sentimiento del consumidor, las expectativas de inflación y la incertidumbre de la política monetaria en los Estados Unidos. Se emplea una muestra de enero de 1998 a enero de 2024, y el trabajo sigue un enfoque VAR (vectorial autorregresivo) basado en el método propuesto por Toda y Yamamoto (1995). La prueba de causalidad de Granger sugiere que las predicciones de la expectativa de inflación basadas en sus propios valores pasados y los valores pasados de la presión de la cadena de suministro global son mejores predicciones de la expectativa de inflación que el uso exclusivo de las observaciones pasadas de la expectativa de inflación. En contraste, las funciones de impulso respuesta sugieren que los aumentos sorpresivos en la presión de la cadena de suministro global conducen a aumentos de las expectativas de inflación y de la incertidumbre de la política monetaria; los efectos de este shock duran hasta dos años. Mientras tanto, las funciones de impulso respuesta sugieren que los aumentos sorpresivos en la presión de la cadena de suministro global disminuyen el sentimiento del consumidor (confianza), y estos efectos duran hasta dos años y medio. Después, el impacto converge de nuevo a cero. Además, los resultados de la descomposición de la varianza sugieren que, en el período final, los impulsos de la presión de la cadena de suministro global explican más del 22%, el 7% y el 44% de la variación del sentimiento del consumidor, la incertidumbre de la política monetaria y las expectativas de inflación, respectivamente.

Palabras clave: *consumidor, expectativas inflacionarias, incertidumbre, métodos macroeconométricos.*
Clasificación JEL: *E210, E310, D800, C500.*

1. Introduction*

In response to the COVID-19 pandemic, governments worldwide took different actions to control this global public health crisis; for example, many governments introduced lockdowns to slow the spread of this contagious disease. These lockdowns implied that suddenly, economic activity stopped almost worldwide. As a result, many governments created different packages to stimulate their economies. For example, the United States and Canada established various programs to provide cash transfers to individuals (Jordà & Nechio, 2023). Another of the main elements of the economic effects of the COVID-19 pandemic is associated with global shipping and transportation costs that surged after the onset of the pandemic. Additionally, delivery times and backlogs spiked to levels with historical proportions; all these factors added significant inflation pressure (Liu & Nguyen, 2023).

Since then, multiple authors have studied the relationship of global supply chain pressure with inflation and its implications for monetary policy decision-making in the United States and Europe (Di Giovanni et al., 2022; Liu & Nguyen, 2023; Kabaca & Tuzcuoglu, 2023; Ascari et al., 2024; Tillmann, 2024). However, attention has not been given to the effects of global supply chain pressure on consumer sentiment, inflation expectation, and monetary policy uncertainty. Nevertheless, attention to inflation expectation has been focused on its relationship with labor-related topics, such as wage growth (Jordà et al., 2022; Jordà & Nechio, 2023). In comparison, attention to consumer sentiment has focused on its relationship with labor market conditions (Herbstman & Brave, 2023). Meanwhile, in the case of economic policy uncertainty (in a broader sense), attention has been given to its viability as a recession predictability tool (Ercolani & Natoli, 2020).

This paper analyzes and studies the effects of global supply chain pressure on consumer sentiment, inflation expectation, and monetary policy uncertainty in the United States, given the lack of attention to the links between global supply chain pressure and these three variables. As a hypothesis, the impulses of global supply chain pressure should increase inflation expectation and monetary policy uncertainty while decreasing consumer sentiment (confidence).

This paper contributes to the literature by examining the impact of global supply chain pressure on critical variables such as consumer sentiment, inflation expectation, and monetary policy uncertainty; these variables are important because they can influence future consumption, savings, and investment, among other variables.

Policy makers at the Federal Reserve System could use this paper's findings to better understand the impact that global supply chain pressure has on variables that can influence consumers' future decisions. Also, suppose global supply chain pressure impulses could increase inflation expectations and monetary policy uncertainty and decrease consumer sentiment (confidence). In that case, it is possible to know how long these possible shocks could last and how sensitive the perceptions of economic agents in the United States are to impulses from this global phenomenon. Our methodological approach uses a Vector Autoregression (VAR) model; in particular, the estimated model is based on the method proposed by Toda and Yamamoto (1995).

This paper is organized as follows: the first section presents a literature review of related studies; the second section presents the methodological literature review; the third section presents the data and methods used in this paper; the fourth section presents the results, and finally, the fifth section presents the concluding remarks.

2. Related Literature

As mentioned before, since the beginning of the COVID-19 pandemic, multiple authors have studied the relationship of global supply chain pressure with inflation in the United States and Europe. For Europe's case, Di Giovanni et al. (2022) found that global supply chain bottlenecks played an outsized role relative to domestic aggregate demand shocks in explaining the inflation experience in this region for 2020–2021. These findings are also similar to the results of Ascari et al. (2024), since these authors found that shocks to global supply chain pressure play a pivotal role in driving post-2020 inflation in the euro area. In another study conducted for 28 European countries, Tillmann (2024) found that increases in supply chain stress could contribute to the movements in the inflation rate during the post-2020 period. Meanwhile, in the case of the United States, Liu and Nguyen (2023) found that global supply chain shocks could significantly affect inflation. Their estimations suggest the effects are relatively short-lived, since they could vanish about 12 months after the impact. Besides, Liu and Nguyen (2023) argue that impulses on the global supply chain pressure that increase inflation could raise inflation expectations and intermediate input costs. Kabaca and Tuzcuoglu (2023) did another analysis for the United States; their results suggest that the global supply chain and oil price shocks are the most significant supply contributors to inflation during the post-2020 period. Additionally, the authors found that demand and supply factors share similar responsibility for the movements in the inflation rate during the post-2020 period.

Discussions about the global supply chain pressure after the COVID-19 pandemic have focused on its implications for inflation rates in the United States and Europe. Additionally, Liu and Nguyen (2023) are the only authors who have suggested that global supply chain pressure could increase inflation expectations. Nevertheless, this hypothesis has not been tested. In contrast, the relationship between inflation expectation and wage growth has been studied in the United States. For example, Jordà et al. (2022) found that since the post-2020 period, inflation expectations have played a more pivotal role in wage-setting dynamics. Something similar was found by Jordà and Nechio (2023) because the authors found that elevated inflation increases the role and importance of inflation expectation on wage-setting dynamics. Furthermore, it is essential to note that the relationship between consumer sentiment and labor market conditions has been studied in the United States. Herbstman and Brave (2023) found that, following the COVID-19 pandemic, consumers' responses to sentiment-surveys' questions are less sensitive to labor market conditions. Regarding economic policy uncertainty, Ercolani and Natoli (2020) built a model using an economic policy uncertainty index (among other variables) to predict recessions. The authors found that macroeconomic and financial uncertainty could play an important role, along with the yield curve slope, in predicting recessions in the United States (Ercolani & Natoli, 2020).

Since the literature has focused on studying the links between global supply chain pressure and inflation, only one study has suggested that global supply chain pressure could increase inflation expectations (Liu & Nguyen, 2023). This paper examines the effects of global supply chain pressure on inflation expectations in the United States and the possible effects of global supply chain pressure with two additional economic agent perception proxies: consumer sentiment and monetary policy uncertainty.

3. Methodological Literature Review

Two of the most common methods used in macroeconomic research are the VAR and Local Projections (LPs) (Sims, 1980; Jordà, 2005). The VAR model resembles a simultaneous equation model since both approaches consider various endogenous variables together (Gujarati & Porter, 2009). Additionally, according to Hamilton (1994), the VAR is a representation of a statistical description of dynamic interrelations between the variables in the model. Besides, the seminal work of Sims (1980) treats the variables symmetrically and evaluates the potential influence of each variable on the other variables that are part of the system (Paramanik & Kamaiah, 2014). It is important to note that within the VARs, multiple types of analysis can be carried out, such as Granger causality, Impulse Response Functions (IRFs), and Variance Decomposition (VD) (Brahmasrene et al., 2014; Rodhan, 2024). However, what are Granger causality, VD, and IRFs? One of the main approaches to causality bases their estimations on predictions (Granger, 1969; Sims, 1972), and causality could be defined in the following way: the predictability at horizon 1 of a given variable X from its past values, the past values of variable Y, and vector Z of auxiliary variables (Dufour & Taamouti, 2010). For the VD case, it could be argued that this method presents if a given shock in one variable accounts for a large share of variation on another variable (Gorodnichenko & Lee, 2020). In contrast, it is possible to infer by its name that IRFs present how a variable responds to impulses from another variable over time. Usually, the estimation of IRFs has been linked to an exercise that requires characterizing the entire dynamic system (Jordà, 2023).

The pioneering contribution of Jordà (2005) showed that the IRFs could be calculated through LPs with a sequence of projections of a series of endogenous variables that are shifted forward through time onto its lags. In addition, Jordà (2005) argues that the VAR could have a significantly poorly specified representation of the data-generating process (DGP), while LPs can be robust to poorly specified DGP. Consequently, Jordà (2005) argues that LPs are a natural and preferable alternative to VARs. Nevertheless, Plagborg-Møller and Wolf (2021) proved that LPs and the VAR model can produce the same IRFs. It is essential to note that Gorodnichenko and Lee (2020) proposed a method to estimate VD through the LPs framework. However, their proposal has not been further developed, while VD continues to be commonly used within the VAR framework. Additionally, Jordà and Taylor (2024) argue that LPs alone cannot uncover causal relations between variables. Since VARs and LPs can produce the same IRFs, there is more body knowledge to estimate VD through VARs, and LPs cannot estimate causality, it was decided to use the VAR as our empirical approach.

Through this methodological (VAR) approach, it is possible to uncover if the global supply chain pressure predicts (Granger causality) inflation expectation, consumer sentiment, and monetary policy uncertainty. Besides, through the IRFs, it is possible to determine how inflation expectation, consumer sentiment, and monetary policy uncertainty respond to global supply chain pressure impulses. In addition, through the VD, it is possible to study if a given shock in the global supply chain pressure accounts for a large share of variation in inflation expectation, consumer sentiment, and monetary policy uncertainty. Hence, through this method, it is possible to uncover the effect of global supply chain pressure on inflation expectation, consumer sentiment, and monetary policy uncertainty in the United States.

Before estimating the VAR model, it is necessary to pay attention to the dynamic structure of the series; therefore, the presence of unit roots is tested. The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are used to test the presence of unit roots in our series (Dickey & Fuller, 1981; Phillips & Perron, 1988). In the case where these tests suggest a similar order of integration between the variables, the Johansen Cointegration Test will be estimated to test the presence of cointegrated equations (Johansen, 1991); if cointegrated equations exist, a VAR with cointegration restrictions will be estimated (Romero-Ramírez, 2023). A standard VAR will be estimated if the Johansen Cointegration Test does not find cointegrating equations. Another possibility that should be considered is that the series might have a different order of integration. Under this scenario, the Toda and Yamamoto (1995) approach will be used to estimate the VAR. Toda and Yamamoto's approach has been widely used to estimate a modified Granger causality test. Nevertheless, the Toda-Yamamoto VAR framework has recently been used to estimate VD and IRFs (Gylych et al., 2020; Kristoufek, 2022). Besides, according to Zapata and Rambaldi (1997), one of the main advantages of the Toda-Yamamoto framework is that it has a limiting chi-squared distribution even if there are no cointegrated equations and the stability/rank conditions are not satisfied.

4. Data and Methods

This paper uses a sample from January 1998 to January 2024. Our sample consists of the following variables: Global Supply Chain Pressure Index, Economic Policy Uncertainty Index: Monetary policy, University of Michigan: Inflation Expectation, and University of Michigan: Consumer Sentiment (FRBNY, 2024; Baker et al., 2024; FRED, 2024a, 2024b). The variables have an index form with a base of 100 in December 2006, and before estimating the tests and the model, the logarithm of each variable is taken; it was decided to specify the model in this way because expected inflation rates and monetary policy uncertainty could vary widely, and taking the logarithm can help mitigate the effects of extreme values.

The Global Supply Chain Pressure Index was first introduced by the work of Benigno et al. (2022); this index captures global supply chain conditions by considering factors associated with global transportation costs and issues related to port congestions and shortages of containers or truck drivers (Kabaca & Tuzcuoglu, 2023). Besides, this index captures information regarding delivery times, backlogs, volume of incomplete orders, and inventory accumulation. Meanwhile, the Economic Policy Uncertainty Index: Monetary Policy (Baker et al., 2024) represents the uncertainty regarding monetary policy discussed in over 2,000 newspapers across the United States. Additionally, the University of Michigan: Inflation Expectation (FRED, 2024b) represents the median expected price change in the next twelve months. For example, if the observation of inflation expectation during March of a given year is 2.3%, consumers expect an inflation rate of 2.3% for March of the following year. In the case of the University of Michigan: Consumer Sentiment (FRED, 2024a), it could be mentioned that it represents a consumer confidence index. An increase in the index is equivalent to an increase in confidence, and a decrease in the index is equivalent to a decrease in consumers' confidence. Now, we turn to describe the empirical methods used in this paper.

Our first step is to employ the unit root tests; as mentioned before, the ADF and PP tests could be used to examine the dynamic structure of our four variables. The ADF and PP tests are defined as in equations 1 and 2, respectively:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-p} + \alpha_i \sum_{i=1}^{m} \Delta Y_{t-p} + \varepsilon_t \tag{1}$$

$$y_t = \tilde{a}_0 + \tilde{a}_1 y_{t-1} + \tilde{a}_1 \left(t - \frac{T}{2} \right) + \mu_t \tag{2}$$

Both tests have an error term (ε_t) and (μ_t), respectively, a trend element (t). Besides, both tests have a null hypothesis that the series are non-stationary. In addition, if the ADF and PP tests suggest that the variables have a similar order of integration, it is necessary to estimate the Johansen Cointegration Test; with this test, it is possible to determine if cointegrated equations exist. There are two tests under the Johansen

Cointegration Test, which are are the Trace and Maximum eigenvalue tests; both are defined as in equations 3 and 4, respectively:

$$J_T = -T \sum_{i=r+1}^{n} \ln\left(-\hat{\lambda}_i\right) \tag{3}$$

$$J_M = -T \ln\left(-\hat{\lambda}_{r+1}\right) \tag{4}$$

The main difference between both tests is that the Trace test checks a null hypothesis of *r* cointegrating vectors against its alternative hypothesis of *n* cointegrating vectors. Meanwhile, the Maximum eigenvalue test examines the null hypothesis of *r* cointegrating vectors against an alternative hypothesis of r+1 cointegrating vectors. In the case in which the Trace and Maximum eigenvalue tests detect the presence of cointegrated equations, it is necessary to estimate a VAR with cointegration restrictions; if both tests do not detect cointegrated equations, it is necessary to estimate a standard VAR that has the following form:

$$gscpi_t = k_{gscpi} + \sum_{i=1}^{12} a_{gscpii} gscpi_{t-i} + \sum_{i=1}^{12} b_{gscpii} mpu_{t-i} + \sum_{i=1}^{12} c_{gscpii} \pi^e{}_{t-i} + \sum_{i=1}^{12} \mathrm{d}_{gscpii} cs_{t-i} + \varepsilon_{gscpit} \tag{5}$$

$$mpu_t = \mathrm{k}_{mpu} + \sum_{i=1}^{12} \mathrm{a}_{mpui} gscpi_{t-i} + \sum_{i=1}^{12} \mathrm{b}_{mpui} mpu_{t-i} + \sum_{i=1}^{12} \mathrm{c}_{mpui} \pi^e{}_{t-i} + \sum_{i=1}^{12} \mathrm{d}_{mpui} cs_{t-i} + \varepsilon_{mput} \tag{6}$$

$$\pi^e{}_t = \mathrm{k}_{\pi^e} + \sum_{i=1}^{12} \mathrm{a}_{\pi^e i} \mathrm{gscpi}_{t-i} + \sum_{i=1}^{12} \mathrm{b}_{\pi^e i} mpu_{t-i} + \sum_{i=1}^{12} \mathrm{c}_{\pi^e i} \pi^e{}_{t-i} + \sum_{i=1}^{12} \mathrm{d}_{\pi^e i} cs_{t-i} + \varepsilon_{\pi^e{}_t} \tag{7}$$

$$cs_t = \mathrm{k}_{cs} + \sum_{i=1}^{12} \mathrm{a}_{csi} gscpi_{t-i} + \sum_{i=1}^{12} \mathrm{b}_{csi} mpu_{t-i} + \sum_{i=1}^{12} \mathrm{c}_{csi} \pi^e{}_{t-i} + \sum_{i=1}^{12} \mathrm{d}_{csi} cs_{t-i} + \varepsilon_{cst} \tag{8}$$

In equations 5, 6, 7, and 8, *t* is time, *gscpi, mpu,* π^e, and *cs* are the logarithms of the Global Supply Chain Pressure Index, Economic Policy Uncertainty Index: Monetary Policy, University of Michigan: Inflation Expectation, and University of Michigan: Consumer Sentiment, respectively; the *k, a, b, c,* and *d* terms are the coefficients that determine how the variables interact. Additionally, $\varepsilon_{gscpit,}$ $\varepsilon_{mput,}$ $\varepsilon_{\pi^e{}_t,}$ and

ε_{cst} are the error terms that capture the variables' unexplained behavior. Finally, suppose the ADF and PP tests (equations 1 and 2) suggest that the variables do not have a similar order of integration. In that case, it is necessary to use the Toda and Yamamoto (1995) method to estimate the VAR system. Where the correct order of the VAR (k) should be augmented by the maximum order of integration (d_{max}), then the system ($k + d_{max}$) is estimated with the coefficients of the last lagged d_{max} vector being ignored.

In summary, this analysis uses a sample from January 1998 to January 2024 that includes the following variables: Global Supply Chain Pressure Index, Economic Policy Uncertainty Index: Monetary Policy, University of Michigan: Inflation Expectation, and University of Michigan: Consumer Sentiment. The four variables have an index form with a base of 100 in December 2006, and the first step is to take the logarithm of each variable. Afterward, the ADF and PP tests are used to test the presence of unit roots. If both tests coincide and the variables have a similar order of integration, estimating the Trace and Maximum eigenvalue tests within the Johansen Cointegration Test is necessary. Additionally, if the Trace and Maximum eigenvalue tests detect the presence of cointegrated equations, estimating a modified VAR with cointegrated restrictions is necessary. On the contrary, if the Trace and Maximum eigenvalue tests do not detect cointegrated equations, estimating a standard VAR is necessary. Finally, suppose the ADF and PP tests suggest that the variables do not have a similar order of integration. In that case, it is necessary to use the Toda and Yamamoto (1995) method to estimate the VAR system.

5. Results

As previously discussed, the first step is to test the presence of unit roots. Two tests are estimated: the ADF and PP tests. The results for both tests can be seen in Tables 1 and 2, respectively (see Table 1 and Table 2). Both tests are estimated using the logarithmic form of our four variables. Additionally, both tests coincide in that the first differences are enough to make the series of consumer sentiment stationary.

Table 1. Unit Root Test–Augmented Dickey-Fuller

Variable	t-Statistic	P-Value	Decision
Global Supply Chain Pressure Index ($gscpi_t$)			Level for $gscpi_t$
Level	-4.3371	0.0005	
University of Michigan: Consumer Sentiment (cs_t)			First Difference for cs_t
Level	-2.4562	0.1274	
1st difference	-15.2694	0.0000	
University of Michigan: Inflation Expectation (π_e^t)			Level for π_e^t
Level	-5.9354	0.0000	
Economic Policy Uncertainty Index: Monetary policy (mpu_t)			Level for mpu_t
Level	-6.1711	0.0000	

Source: Prepared by the author.

Nevertheless, the ADF and PP tests also coincide with the fact that the global supply chain pressure, inflation expectation, and monetary policy uncertainty are already stationary at levels. Given that the variables do not have a similar order of integration, the Johansen cointegration tests will not be estimated, and the Toda and Yamamoto (1995) method is used to estimate the VAR system.

Table 2. Unit Root Test – Phillips-Perron

Variable	t-Statistic	P-Value	Decision
Global Supply Chain Pressure Index ($gscpi_t$)			Level for $gscpi_t$
Level	-4.3611	0.0004	
University of Michigan: Consumer Sentiment (cs_t)			First Difference for cs_t
Level	-2.7419 -	0.0682	

Variable	t-Statistic	P-Value	Decision
1st difference	-18.5592	0.0000	
University of Michigan: Inflation Expectation (π_t^e)			Level for π_t^e
Level	-5.7702	0.0000	
Economic Policy Uncertainty Index: Monetary policy (mpu_t)			Level for mpu_t
Level	-7.9438	0.0000	

Source: Prepared by the author.

Under the modified version of the VAR of Toda and Yamamoto (1995), the optimal lag order must be determined, additional tests must be estimated, and the stability condition must be satisfied. Table 3 presents the results for the VAR Lag Order Selection Criteria (see Table 3). These results suggest that one or three are the optimal lag order for the VAR. The Lagrange Multiplier (LM) test is estimated to determine which of these two options is the appropriate lag order. These results can be seen in Table 4 (see Table 4). Additionally, the VAR Residual Serial Correlation LM Test results suggest that only three lags passed the LM test.

In addition, the final preliminary step before estimating the Toda-Yamamoto VAR is to determine if the system satisfies the stability condition. Table 5 suggests that the VAR system satisfies the stability condition since no root lies outside the unit circle (see Table 5). The Toda-Yamamoto augmented VAR uses the maximum order of integration of the variables (d_{max}) for estimation purposes. These estimates can be seen in Table A1 of the Appendix (see Table A1); the next step is the estimations of the Granger causality test; these results can be seen in Table 6 (see Table 6).

The results of the Granger causality test suggest that the predictions of inflation expectation based on its past values and the past values of the global supply chain pressure are better predictions of inflation expectation than just using the past observations of inflation expectation. In addition, another unidirectional Granger causality relationship was found between monetary policy uncertainty and consumer sentiment. Finally, a bi-directional Granger causality relationship was found between inflation expectation and monetary policy uncertainty. As mentioned before, in this study, the IRFs are estimated within the VAR framework, and these results can be seen in Figure 1 (see Figure 1).

Table 3. VAR Lag Order Selection Criteria

Endogenous variables: cs_t, mpu_t, $gscpi_t$, π^e_t

Exogenous variables: C

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-189.2130	NA	4.17e-05	1.266971	1.315762	1.286486
1	600.0515	1552.652	2.62e-07	-3.803617	-3.559662*	-3.706040*
2	609.3122	17.97483	2.74e-07	-3.759424	-3.320305	-3.583786
3	636.8055	52.64298	2.54e-07*	-3.834790*	-3.200508	-3.581091
4	644.1414	13.85403	2.69e-07	-3.777977	-2.948530	-3.446215
5	660.5447	30.54768	2.68e-07	-3.780621	-2.756010	-3.370798
6	675.8957	28.18542*	2.70e-07	-3.776365	-2.556591	-3.288481
7	686.6024	19.37740	2.79e-07	-3.741655	-2.326717	-3.175709
8	695.8659	16.52246	2.92e-07	-3.697481	-2.087379	-3.053474

*Indicated lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level). FPE: Final prediction error. AIC: Akaike information criterion. SC: Schwarz information criterion. H.Q.: Hannan-Quinn information criterion.

Source: Prepared by the author.

Table 4. VAR Residual Serial Correlation LM Test

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	P-Value	Rao F-stat	df	P-Value
1	46.81033	16	0.0001	2.979173	(16, 901.9)	0.0001
2	55.216114	16	0.0000	3.530589	(16, 901.9)	0.0000
3	25.44836	16	0.0623	1.600576	(16, 901.9)	0.0623
4	16.74918	16	0.4020	1.048392	(16, 901.9)	0.4020
5	23.91553	16	0.0914	1.502895	(16, 901.9)	0.0914
6	22.94956	16	0.1151	1.441422	(16, 901.9)	0.1151

Source: Prepared by the author.

Table 5. Roots of Characteristic Polynomial

Endogenous variables: cs_t, mpu_t, $gscpi_t$, π_t^e

Exogenous variables: C

Root	Modulus
0.935601	0.935601
0.854195	0.854195
0.736511 - 0.065176i	0.739389
0.736511 + 0.065176i	0.739389
-0.209585	0.209585
0.100676	0.100676
-0.040183	0.040183
0.002730	0.002730
No root lies outside the unit circle	
VAR satisfies the stability condition	

Source: Prepared by the author.

Table 6. VAR Granger Causality/Block Exogeneity Wald Tests

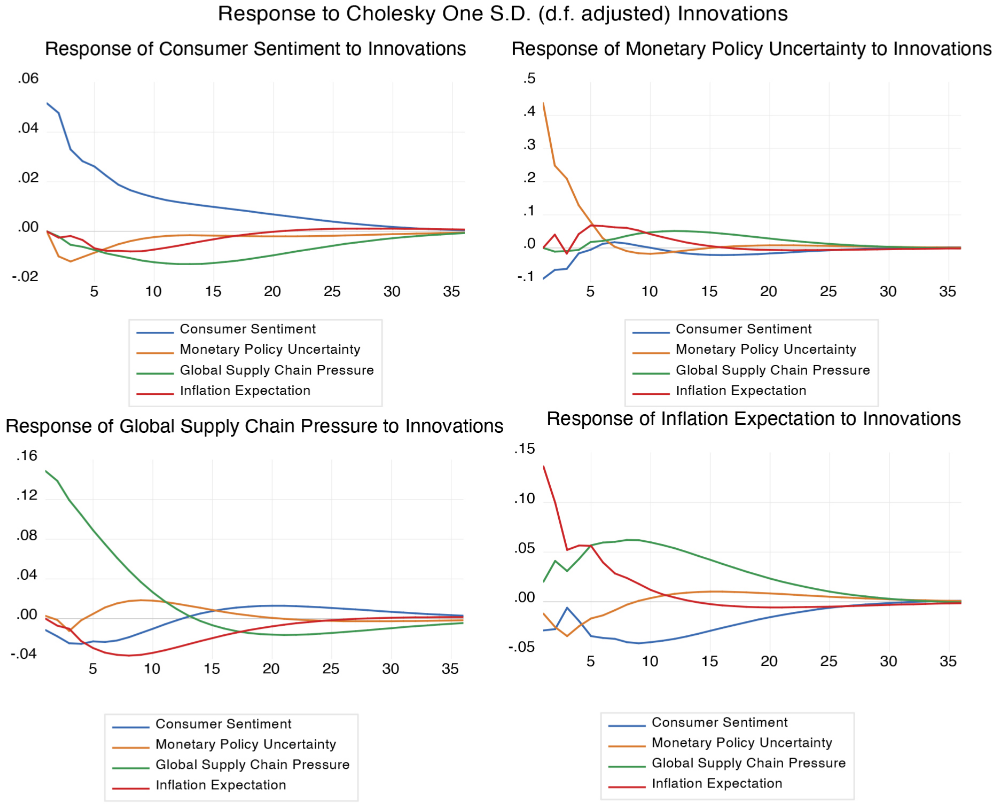
Null Hypothesis	Chi-sq	df	P-Value	Decision	Type of Causality
π_t^e does not Granger Cause $gscpi_t$	3.306509	3	0.3467	Do not reject	
$gscpi_t$ does not Granger Cause π_t^e	15.95594	3	0.0012	Reject	Unidirectional causality from $gscpi_t$ to π_t^e
mpu_t does not Granger Cause $gscpi_t$	3.112165	3	0.3747	Do not reject	
$gscpi_t$ does not Granger Cause mpu_t	0.458230	3	0.9280	Do not reject	No causality
$gscpi_t$ does not Granger Cause cs_t	1.969270	3	0.5788	Do not reject	

Null Hypothesis	Chi-sq	df	P-Value	Decision	Type of Causality
cs_t does not Granger Cause	3.309378	3	0.3463	Do not reject	No causality
mpu_t does not Granger Cause π_t^e	9.036219	3	0.0288	Reject	
π_t^e does not Granger Cause mpu_t	8.470725	3	0.0372	Reject	Bi-directional causality
cs_t does not Granger Cause mpu_t	1.540739	3	0.6729	Do not reject	
mpu_t does not Granger Cause cs_t	13.08185	3	0.0045	Reject	Unidirectional causality from mpu_t to cs_t
cs_t does not Granger Cause π_t^e	2.860959	3	0.4136	Do not reject	
π_t^e does not Granger Cause cs_t	2.209512	3	0.5301	Do not reject	No causality

Source: Prepared by the author.

Figure 1 presents how the global supply chain pressure, monetary policy uncertainty, inflation expectation, and consumer sentiment respond over time to a surprise increase from all the variables that are part of the system. In the case of global supply chain pressure, the results suggest that a surprise increase in this variable leads to an increase in monetary policy uncertainty that peaks between 10 and 15 months after the impulses (see Figure 1). Besides, the effects of global supply chain pressure on monetary policy uncertainty statistically vanish about two years after the initial surprise increase. For the inflation expectation case, the results suggest that a surprise increase in the global supply chain pressure leads to an increase in inflation expectation that reaches its peak ten months after the impact, and its effects converge back to zero two years after the shock. Our final case concerns the consumer sentiment response to global supply chain pressure shocks. These results suggest that a surprise increase in global supply chain pressure decreases consumer sentiment (confidence); the effects of this impact converge back to zero two and a half years after the initial shock.

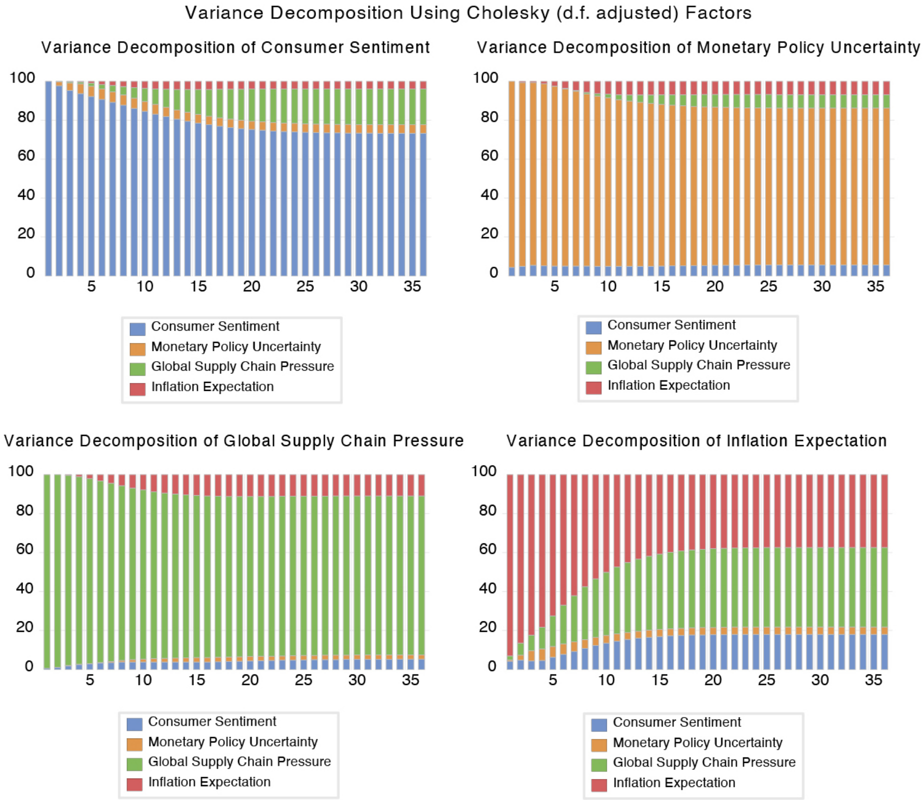
Figure 1. Impulse Response Functions



Source: Prepared by the author.

Besides, it is essential to note that five months after the initial surprise increases in global supply chain pressure, this last variable became the one that led to the most significant decreases in consumer sentiment and the biggest increases in inflation expectation. Meanwhile, it became the variable that led to the most significant increases in monetary policy uncertainty ten months after the initial surprise increase. Afterward, the effects of these impacts converge back to zero. In addition, it is essential to note that, as expected, surprise increases in consumer sentiment, monetary policy uncertainty, and inflation expectation lead to smaller (compared to the other IRFs results) effects on global supply chain pressure. Figure 2 presents the results of VD for the four variables that are part of the VAR system (see Figure 2).

Figure 2. Variance Decompositions



Source: Prepared by the author.

Figure 2 shows the VD of consumer sentiment, monetary policy uncertainty, global supply chain pressure, and inflation expectation over time (see Figure 2). These results suggest that by the final period, the impulses of the global supply chain pressure explain over 22%, 7%, and 44% of the variation of consumer sentiment, monetary policy uncertainty, and inflation expectation, respectively. However, the impulses of consumer sentiment and monetary policy uncertainty are the primary sources of their own variation. At the same time, the global supply chain pressure explains the higher percentage of variation of inflation expectation by the final period. Therefore, global supply chain pressure shocks may not be responsible for significant variations in inflation expectations in the short run, but may cause longer-term fluctuations.

Meanwhile, shocks from the global supply chain pressure may be responsible for lower percentages of variations of monetary policy uncertainty and consumer sentiment in the short-run and longer-term. In addition, as expected during practically the entire period, consumer sentiment, monetary policy uncertainty, and inflation expectations explain minimal percentages of global supply chain pressure variations.

6. Concluding Remarks

This paper studies the effects of global supply chain pressure on consumer sentiment, inflation expectations, and monetary policy uncertainty. A sample from January 1998 to January 2024 is used, and this paper follows a VAR approach based on the method proposed by Toda and Yamamoto (1995). The Granger causality test suggests that the predictions of inflation expectation based on its own past values and the past values of global supply chain pressure are better predictions of inflation expectation than just using the past observations of inflation expectation. Meanwhile, the IRFs suggest that a surprise increase in the global supply chain pressure increases inflation expectations and monetary policy uncertainty, which can last up to 24 months. Besides, the IRFs suggest that surprise increases in the global supply chain pressure decrease consumer sentiment (confidence), lasting up to 30 months. Afterward, the impact converges back to zero.

Additionally, the VD results suggest that by the final period, the impulses of the global supply chain pressure explain over 22%, 7%, and 44% of the variation of consumer sentiment, monetary policy uncertainty, and inflation expectation, respectively. Nevertheless, the impulses of consumer sentiment and monetary policy uncertainty are the primary sources of their own variation. At the same time, the global supply chain pressure explains the higher percentage of variation of inflation expectation by the final period. Policy makers at the Federal Reserve System should monitor the impact of global supply chain pressure on consumer sentiment, inflation expectation, and monetary policy uncertainty, since the last three variables are crucial elements that could influence future consumption, savings, investment, and monetary policy decisions.

* The views in this paper are solely the responsibility of the author and should not be interpreted as reflecting the views of the Federal Reserve Bank of San Francisco or the Board of Governors of the Federal Reserve System.

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https://doi.org/10.36105/theanahuacjour.2024v24n2.2515

Appendix

Table A1. VAR Estimates

Standard errors in ( ) and t-statistics in [ ]

cs_t (-1)	0.867324	-0.115348	-0.185020	-0.158974
	(0.06135)	(0.53155)	(0.17746)	(0.16791)
	[14.1376]	[-0.21700]	[-1.04258]	[-0.94678]
cs_t (-2)	-0.186662	-0.256670	-0.083465	0.284784
	(0.08008)	(0.69386)	(0.23165)	(0.21918)
	[-2.33090]	[-0.36992]	[-0.36030]	[1.29930]
cs_t (-3)	0.131634	0.816321	0.095116	-0.331055
	(0.08017)	(0.69462)	(0.23191)	(0.21942)
	[1.64195]	[1.17521]	[0.41015]	[-1.50876]
mpu_t (-1)	-0.023650	0.577623	-0.010623	-0.039610
	(0.00691)	(0.05984)	(0.01998)	(0.01890)
	[-3.42431]	[9.65266]	[-0.53172]	[-2.09540]
mpu_t (-2)	0.005317	0.149571	-0.026344	-0.019964
	(0.00791)	(0.06850)	(0.02287)	(0.02164)
	[0.67257]	[2.18355]	[-1.15196]	[-0.92264]
mpu_t (-3)	0.002826	-0.070795	0.029849	0.036630
	(0.00783)	(0.06786)	(0.02266)	(0.02144)
	[0.36078]	[-1.04321]	[1.31746]	[1.70873]
$gscpi_t$ (-1)	-0.011424	-0.115583	0.940879	0.177122
	(0.02048)	(0.17741)	(0.05923)	(0.05604)
	[-0.55794]	[-0.65148]	[15.8847]	[3.16044]
$gscpi_t$ (-2)	-0.013319	0.072852	-0.065818	-0.147091
	(0.02784)	(0.24121)	(0.08053)	(0.07619)
	[-0.47845]	[0.30203]	[-0.81733]	[-1.93047]

$gscpi_t$ (-3)	0.009583	0.026983	0.017355	0.131332
	(0.02802)	(0.24274)	(0.08104)	(0.07668)
	[0.34207]	[0.11116]	[0.21416]	[1.71279]
π_t^e (-1)	-0.018867	0.293126	-0.052345	0.731434
	(0.02189)	(0.18967)	(0.06332)	(0.05992)
	[-0.86185]	[1.54544]	[-0.82663]	[12.2078]
π_t^e (-2)	0.022768	-0.519764	0.011816	-0.134230
	(0.02652)	(0.22975)	(0.07670)	(0.07257)
	[0.85866]	[2.26234]	[0.15406]	[-1.84956]
π_t^e (-3)	-0.033021	0.591893	-0.084917	0.243334
	(0.02652)	(0.22979)	(0.07672)	(0.07259)
	[-1.24512]	[2.57584]	[-1.10690]	[3.35231]
C	0.762385	0.197212	1.286738	1.273169
	(0.19057)	(1.65116)	(0.55126)	(0.52158)
	[4.00059]	[0.11944]	[2.33419]	[2.44097]
cs_t (-4)	0.096730	-0.397300	0.107694	0.106657
	(0.05858)	(0.50753)	(0.16945)	(0.16032)
	[1.65133]	[-0.78281]	[0.63557]	[0.66526]
mpu_t (-4)	0.005775	0.068113	-0.003981	0.003046
	(0.00702)	(0.06080)	(0.02030)	(0.01921)
	[0.82287]	[1.12023]	[-0.19612]	[0.15861]
$gscpi_t$ (-4)	-0.002731	-0.031195	0.017902	-0.071791
	(0.02082)	(0.18039)	(0.06022)	(0.05698)
	[-0.131116]	[-0.17293]	[0.29725]	[-1.25986]
π_t^e (-4)	-0.016090	-0.043338	0.017985	-0.084708
	(0.02164)	(0.18746)	(0.06259)	(0.05922)
	[-0.74366]	[-0.23118]	[0.28736]	[-1.43045]

R-squared	0.915608	0.491492	0.805728	0.692582
Adj. R-squared	0.910984	0.463629	0.795083	0.675737
Sum sq. resids	0.777866	58.39592	6.508989	5.827075
S.E. equation	0.051613	0.447198	0.149302	0.141265
F-statistic	198.0030	17.63934	75.69049	41.11543
Log-likelihood	486.1599	-181.0403	157.9423	175.0406
Akaike AIC	-3.036633	1.281814	-0.912248	-1.022917
Schwarz SC	-2.831239	1.487208	-0.706854	-0.817522
Mean dependent	4.510982	6.082081	4.748457	4.635519
S.D. dependent	0.172992	0.610615	0.329820	0.248076
Determinant resid covariance (dof adj.)		2.10E-07		
Determinant resid covariance		1.67E-07		
Log-likelihood		657.0981		
Akaike information criterion		-3.812933		
Schwarz criterion		-2.991356		
Number of coefficients		68		

Source: Prepared by the author.

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About the author

Héctor Romero-Ramírez holds a Master's in Economics from the University of Puerto Rico, Río Piedras. He is also an alumnus of the American Economic Association Summer Program, where he took doctoral courses at Howard University. Additionally, he has worked as an Economic Advisor to the Finance Committee of the Senate of Puerto Rico and as a Research Associate at the Federal Reserve Bank of San Francisco. Romero-Ramírez is the author of papers published in peer-reviewed journals.

hector.romero-ramirez@sf.frb.org; hromero9722@gmail.com
https://orcid.org/0000-0002-0765-9524