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Time-varying Granger Causality Between Health Care and Economic Activity in the United States

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Abstract The COVID-19 epidemic has led to the need to analyse the relationship between health care and the economy. This paper analyses the time-varying relationship between health care and economic activity in the United States, filling a gap in the literature. Using time-varying Granger causality, the study provides empirical evidence of a time-varying causal relationship between health care spending and industrial production, which has important policy implications.

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1 Introduction

Access to health care is a hot topic in the United States (Chen, 2025; Cuadros et al., 2023; Dobkin et al., 2018; Flores Morales, 2024), which has a mixed health care system (Curto et al., 2019; Oberlander, 2002). A mixed health care system is a health care system in which health care is provided by both private and public health care providers. Americans generally believe that private health care providers provide better health care than public health care providers, which means that access to better health care depends on income and wealth (Berwick et al., 2025; Hoffman & Paradise, 2008; Flores Morales, 2024; see also Schwandt, 2018). In recent years, especially after the Covid-19 outbreak, health economists have become increasingly interested in analysing the relationship between health care and the economy (see Rasul, 2020). This paper analyses the time-varying relationship between health care and economic activity in the United States, filling a gap in the literature.

Using time-varying Granger causality, the study provides empirical evidence for a time-varying causal relationship between health care spending and industrial production, which has important policy implications. Furthermore, it contributes to the discussion on the impact of the COVID-19 epidemic on the economy and vice versa.

The remainder of this paper is organised as follows. Section 2 reviews the literature on the relationship between health care and the economy, Section 3 describes the methods and data, Section 4 presents the results, Section 5 discusses the results, and Section 6 concludes the paper.

2 Literature review

The outbreak and spread of the SARS-CoV-2 coronavirus, which causes COVID-19, has shown how important good health care is for the normal functioning of the economy (Fiori & Iacoviello, 2021; Sexton & Tito, 2021; Terry, 2020). The COVID-19 epidemic and the measures taken to contain the spread of the SARS-CoV-2 coronavirus (e.g. lockdowns) led to disruptions in trade and production and caused a shortage of goods, which had a negative impact on economic activity (Antioch, 2024; Caldara et al., 2025; Dunn, 2021; Ihrig et al., 2020). Although the COVID-19 recession lasted only two months, from March to April 2020, it had a negative impact on the health care sector (Rhyan et al., 2020). One reason for this was a decrease in health care expenditure due to an increase in the unemployment rate (Rhyan et al., 2020). Although this phenomenon was temporary, the same cannot be said of inflation (Cuba-Borda et al., 2025; Lipińska et al., 2025), which peaked in 2022 (Faria-e-Castro, 2025). It not only had a negative impact on the health care sector (higher prices, higher costs), but also on health (higher costs, higher stress levels) (Fiedler, 2022; Movsisyan et al., 2024). In addition, the higher prices for health care services led to an increase in inflation (Fiedler, 2022). Research by Hildebrandt and Thomas (1991) shows that inflation can affect the prices of health care services and vice versa (see also Glied, 2003). However, inflation does not affect all participants in the health care market equally (Fiedler, 2022). According to Prager (2020), some of them adapt by seeking a cheaper health care provider in another US state or abroad. High health care costs can also discourage people from seeing a doctor, which in the worst case can even jeopardise their lives (Hamilton et al., 2018).

The problem is that there is little research that examines the relationship between health care and economic activity before the outbreak of the SARS-CoV-2 coronavirus. This shows that the COVID-19 epidemic was a turning point (see Murray, 2020). This is because the COVID-19 crisis was not only a health crisis, but also an economic crisis (Clarida et al., 2021; Knotek et al., 2020). According to von der Schulenburg (2021), the COVID-19 epidemic has led health economists to assess the direct and indirect costs and benefits of health policy measures (e.g. vaccination measures). In the past, research on the relationship between health care and economic activity has focused primarily on the impact of industrial production on occupational health (for a literature review, see Belzer & Quinlan, 2024), which is only a small part of the overall picture. This also applies to the impact of health on workplace absenteeism (for a literature review, see Lee et al., 2023). Research by Fisman et al (2024) shows that flu or flu-like illness can reduce working hours and productivity. This was also the case during the COVID-19 epidemic (Bloom et al., 2025; see also Groenewold et al., 2020).

Research by Vysochyna et al. (2023) shows that the outbreak and spread of the SARS-CoV-2 coronavirus has also led to an increase in health care spending (both in the private and public sectors), which has had a positive impact on economic growth and health outcomes. Although the results were not immediately visible, they contributed to a faster economic recovery after the COVID-19 outbreak.

During the COVID-19 epidemic, uncertainty has become the new normal. The health crisis has increased health policy uncertainty, while the economic crisis has increased economic policy uncertainty (Altig et al., 2020; Barrero & Bloom, 2020). Both had a negative impact on the economy and put additional pressure on economic agents. Similar to economic policy uncertainty (see Baker et al., 2016), health policy uncertainty can affect the employment and investment decisions of health care providers, which in turn can have a negative impact on economic activity.

3 Methods and data

The empirical study aims to analyse the time-varying causal relationships between health care and economic activity in the United States. Health care is represented by health-related absenteeism rate of employees ($ABSrate_t$), personal health expenditure ($lnHEXP_t$) and health policy uncertainty ($HEPU_t$), while economic activity is represented by industrial production activity ($lnIP_t$). The econometric framework used is the vector autoregression model (VAR), which can also be used to control for other variables that could influence the causal relationship between the variables analysed. In particular, we resort to a macroeconomic VAR that controls for the general price level ($lnCPI_t$) and monetary policy ($MPrate_t$), which can be written as follows:

$$\begin{aligned}
HEPU_t &= a_1 + b_{11}HEPU_{t-1} + b_{12}HEPU_{t-2} + b_{13}lnIP_{t-1} + \\
&b_{14}lIP_{t-2} + b_{15}HEXP_{t-1} + b_{16}lnHEXP_{t-2} + b_{17}lnCPI_{t-1} + \\
&b_{18}lnCPI_{t-2}+b_{19}MPrate_{t-1}+b_{110}MPrate_{t-2} + \\
&b_{111}ABSrate_{t-1}+b_{112}ABSrate_{t-2} + e_{1t} \\
\\
lnIP_t &= a_2 + b_{21}HEPU_{t-1} + b_{22}HEPU_{t-2} + b_{23}lnIP_{t-1} + b_{24}lIP_{t-2} + \\
&b_{25}HEXP_{t-1} + b_{26}lnHEXP_{t-2} + b_{27}lnCPI_{t-1} + \\
&b_{28}lnCPI_{t-2}+b_{29}MPrate_{t-1}+b_{210}MPrate_{t-2} + \\
&b_{211}ABSrate_{t-1}+b_{212}ABSrate_{t-2} + e_{2t} \\
\\
HEXP_t &= a_3 + b_{31}HEPU_{t-1} + b_{32}HEPU_{t-2} + b_{33}lnIP_{t-1} + \\
&b_{34}lIP_{t-2} + b_{35}HEXP_{t-1} + b_{36}lnHEXP_{t-2} + b_{37}lnCPI_{t-1} +
\end{aligned} \qquad (1),$$

$$b_{38}lnCPI_{t-2}+b_{39}MPrate_{t-1}+b_{310}MPrate_{t-2}+$$
$$b_{311}ABSrate_{t-1}+b_{312}ABSrate_{t-2}+e_{3t}$$

$$lnCPI_t=a_4+b_{41}HEPU_{t-1}+b_{42}HEPU_{t-2}+b_{43}lnIP_{t-1}+$$
$$b_{44}lIP_{t-2}+b_{45}HEXP_{t-1}+b_{46}lnHEXP_{t-2}+a_{47}lnCPI_{t-1}+$$
$$b_{48}lnCPI_{t-2}+b_{49}MPrate_{t-1}+b_{410}MPrate_{t-2}+$$
$$b_{411}ABSrate_{t-1}+b_{412}ABSrate_{t-2}+e_{4t}$$

$$MPrate_t=a_5+b_{51}HEPU_{t-1}+b_{52}HEPU_{t-2}+b_{53}lnIP_{t-1}+$$
$$b_{54}lIP_{t-2}+b_{55}HEXP_{t-1}+b_{56}lnHEXP_{t-2}+b_{57}lnCPI_{t-1}+$$
$$b_{58}lnCPI_{t-2}+b_{59}MPrate_{t-1}+b_{510}MPrate_{t-2}+$$
$$b_{511}ABSrate_{t-1}+b_{512}ABSrate_{t-2}+e_{5t}$$

$$ABSrate_t=a_6+b_{61}HEPU_{t-1}+b_{62}HEPU_{t-2}+b_{63}lnIP_{t-1}+$$
$$b_{64}lIP_{t-2}+b_{65}HEXP_{t-1}+b_{66}lnHEXP_{t-2}+b_{67}lnCPI_{t-1}+$$
$$b_{68}lnCPI_{t-2}+b_{69}MPrate_{t-1}+b_{610}MPrate_{t-2}+$$
$$b_{611}ABSrate_{t-1}+b_{612}ABSrate_{t-2}+e_{6t}$$

where $a_n(n=1,\dots,6)$ are estimated constants, b_{nk} $(n=1,\dots,6;k=1,\dots,mn)$ are estimated parameters, and e_{nt} $(n=1,\dots,6)$ is an error term. We use the above specification to determine optimal value of m (which is 2 in the above specification) by estimating the information criteria by standard Stata routines (see the results below)[1].

Typically, testing for Granger causality between two specific variables rests on joint Wald test of the zero-value null hypothesis of specific pairs of b_{nk} parameters, e.g. testing whether $HEPU_t$ Granger causes $HEXP_t$ is a Wald test of the null hypothesis $b_{31}=b_{32}=0$. In this context it is also usually assumed that the variables in the VAR model specification are stationary, unless lag-augmentation is used as suggested by Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996), which leads to a lag-adjusted VAR (LA-VAR). This is achieved by adding d additional lags to the m lags in equation (1) above, where d is the largest order of integration of one of the

[1] We also estimate an alternative model in which a time trend is added to model (1) as an exogenous variable.

variables of the VAR model and is determined by unit root tests (see e.g. Baum et al., 2025; Shi et al., 2018; Shi et al., 2020). We apply the ADFmax test by Leybourne (1995) and the DF-GLS test by Elliott, Rothenberg and Stock (1996) using the adfmaxur-Stata code by Otero and Baum (2018) and the ersur code by Otero and Baum (2017).

While the procedure described above is used to obtain a single, static estimate of a Wald test statistic, Shi et al. (2018), Shi et al. (2020) and Baum et al. (2025) have proposed a method for computing the time-varying Granger causality test statistic based on three recursive (sequential) methods of test statistic estimation, implemented in the tvgc Stata code of Baum et al. (2022) and used in this study – the forward expanding method (FE, in which the test statistic is computed from the VAR model on subsamples expanding from the first observation through a certain minimum specified window size to the maximum possible window size), the rolling window method (RO, which involves an estimation of VARs on subsamples of a given window size that rolls forward) and the recursive evolving method (RE, which is similar to the FE method except that the starting point of the estimation can be any time period t in the sample). All methods result in a time series of Wald statistics or, alternatively, a single statistic for the test of the entire sample with the null hypothesis that a given variable does not Granger cause another variable at any point in time (Baum et al., 2022). For the time-varying Granger analysis, the minimum window size is set to 72 months (as suggested by Baum et al., 2022, 2025) and the critical significance levels for the test statistics are calculated using a bootstrap technique (500 replications are used), as suggested by Shi et al. (2018) and Shi et al. (2020), and it controls for size (i.e., the problem of multiplicity – see Shi et al. 2020) by including 12 observations in the calculation, as suggested by Baum et al. (2022). As suggested by Baum et al. (2022), we also include a time trend in the Granger causality test, as some variables exhibit trend development. Heteroskedasticity robust test statistics are used as recommended by Shi et al. (2018). Finally, the test statistics and critical significance levels are presented graphically.

The variables in model (1) are monthly and cover the period 1990m1–2025m3. Variables defined in percentages ($MPrate_t$, and $ABSrate_t$) and $HEPU_t$ enter the model in levels while other variables in natural logarithms of levels. All variables except $HEPU_t$ and $MPrate_t$ are seasonally adjusted. A detailed description and the data sources can be found in Table 1, while descriptive statistics are in Table 2.

Table 1: Time series description

Notation	Description and data source
$HEPU_t$	Health Policy Uncertainty index, monthly frequency. Health care categorical Economic Policy Uncertainty index for the US computed by Baker et al. (2016) is used, accessed at webpage https://www.policyuncertainty.com/categorical_epu.html.
$lnIP_t$	Natural logarithm of industrial production (total) index, real (quantity) values, monthly frequency, seasonally adjusted. Data source is Board of Governors of the Federal Reserve System (2025a).
$lnHEXP_t$	Natural logarithm of personal health expenditures index, real (quantity) values, monthly frequency, seasonally adjusted. Data source is U.S. Bureau of Economic Analysis (2025).
$lnCPI_t$	Natural logarithm of consumer price index, monthly frequency, seasonally adjusted. Data source is U.S. Bureau of Labor Statistics (2025a).
$MPrate_t$	Monetary policy rate in the US. For the period 1990m1-2022m2 this is the shadow federal funds rate computed by Wu-Xia (2016), for the period 2022m3-2025m3 the federal funds effective rate is used. Data source for the first is Federal Reserve Bank of Atlanta (2022) while for the second Board of Governors of the Federal Reserve System (2025b)
$ABSrate_t$	Rate of health-related absenteeism from work, monthly frequency, seasonally adjusted. The variable is calculated as follows. First, we used data from the Current Population Survey and summed two categories of employed persons who did not work in the reference week of the study for health reasons: i) those who did not work at all (data source: U.S. Bureau of Labor Statistics, 2025b) and ii) those who worked only part of the time (data source: U.S. Bureau of Labor Statistics, 2025c). Second, the calculated number of employees who were absent for health reasons was divided by the number of employees who normally work full-time (U.S. Bureau of Labor Statistics, 2025d) and multiplied by 100 to obtain the absence rate as a percentage. Third, since the time series in the previous steps were not seasonally adjusted, the time series obtained in the second step was seasonally adjusted (the seasonal adjustment was performed for the entire available time series, which ranges from 1976m6 to 2025m3) using the JDemetra+ X-13 adjustment method and the X11 specification of the Eviews software.

Table 2: Descriptive statistics of model´s variables

Variable	Number of observations	Mean value	Standard deviation	Minimum value	Maximum value
$HEPU_t$	423	146.9286	118.4311	15.28183	1030.681
$lnIP_t$	423	4.490351	0.1598244	4.099288	4.645823
$lnHEXP_t$	423	4.332502	0.2765698	3.881976	4.86534
$lnCPI_t$	423	5.308373	0.2398394	4.848116	5.767618
$MPrate_t$	423	2.468889	2.742331	–2.99	8.14
$ABSrate_t$	423	2.62157	0.4003649	1.656403	5.449699

Source: Own calculations.

4 Results

To determine the optimal lag structure of model (1), two unit root tests and lag selection are performed. Following Baum et al. (2025), the ADFmax test by Leybourne (1995) and the DF-GLS test by Elliott, Rothenberg, and Stock (1996) were used, both based on a Dickey-Fuller type of test specification, which according to the authors perform better than the adjusted DF test (Dickey and Fuller, 1979). The results, presented in Tables 3 and 4, indicate that $HEPU_t$ is a stationary time series, $lnIP_t$ is trend stationary, while $lnHEXP_t$, $lnCPI_t$, $MPrate_t$, and $ABSrate_t$ are I(1) time series (the results show that the time series only become stationary when the time series are differenced). A mixture of I(0) and I(1) suggests that the VAR specification for the Granger test (1) needs to be extended by an additional lag of the explanatory variables (see Baum et al., 2025; Dolado & Lütkepohl, 1996; Toda & Yamamoto, 1995).

Table 3: Results of ADFmax (Leybourne, 1995) unit root test

Variable		Test results – model with a constant (in brackets with constant plus trend)			
		Inf. criteria	Lags included	Test statistics	p-value
$HEPU_t$	In level	AIC	3 (0)	–4.371 (–6.854)	0.000 (0.000)
		SIC	0 (0)	–6.251 (–6.854)	0.000 (0.000)

$lnIP_t$	In level	AIC	2 (2)	0.867 (–1.082)	0.986 (0.861)
		SIC	2 (2)	0.867 (–1.082)	0.989 (0.861)
	In first difference	AIC	1 (1)	–14.806 (–14.926)	0.000 (0.000)
		SIC	1 (1)	–14.806 (–14.926)	0.000 (0.000)
$lnHEXP_t$	In level	AIC	7 (2)	0.473 (–4.182)	0.966 (0.004)
		SIC	2 (2)	0.026 (–4.182)	0.917 (0.002)
	In first difference	AIC	6 (6)	–10.830 (–10.850)	0.000 (0.000)
		SIC	1 (1)	–20.004 (–19.989)	0.000 (0.000)
$lnCPI_t$	In level	AIC	15 (15)	0.245 (–2.145)	0.943 (0.370)
		SIC	2 (3)	0.478 (–1.291)	0.970 (0.787)
	In first difference	AIC	14 (14)	–3.688 (–3.669)	0.002 (0.017)
		SIC	1 (1)	–12.030 (–12.015)	0.000 (0.000)
$MPrate_t$	In level	AIC	6 (6)	–2.333 (–2.908)	0.070 (0.103)
		SIC	4 (4)	–1.859 (–2.296)	0.163 (0.274)
	In first difference	AIC	5 (5)	–4.612 (–4.667)	0.000 (0.001)
		SIC	3 (3)	–5.889 (–5.965)	0.000 (0.000)
$ABSrate_t$	In level	AIC	8 (8)	–1.708 (–2.483)	0.225 (0.225)
		SIC	4 (4)	–2.520 (–3.623)	0.039 (0.013)
	In first difference	AIC	7 (7)	–11.355 (–11.342)	0.000 (0.000)
		SIC	4 (4)	–15.238 (–15.218)	0.000 (0.000)

Notes: The ADFmax test by Leybourne (1995) was performed using the adfmaxur Stata codes by Otero and Baum (2018). For each variable included in the Granger model, the null hypothesis of the unit root is tested against the alternative for the level and first difference of a variable. The test is based on ADF-type regressions in which we have the number of lags determined by Akaike (AIC) and Schwarz Information Criteria (SIC) (the maximum number of lags in our case is 17 and is determined by the method of Schwert (1989). The test regression is estimated once with a constant only and once with a constant plus trend (results in brackets). The last two columns show the test statistics and the p-value of the statistics. See Leybourne (1995) and Baum and Otero (2018) for details on the test and the software code features.

Source: Own calculations.

Table 4: Results of DF-GLS (Elliot et al., 1996) unit root test

Variable		Test results – model with a constant (in brackets with constant plus trend)			
		Inf. criteria	Lags included	Test statistics	p-value
$HEPU_t$	In level	AIC	3 (3)	–4.045 (–4.636)	0.000 (0.000)
		SIC	0 (0)	–5.928 (–6.436)	0.000 (0.000)
$lnIP_t$	In level	AIC	11 (2)	0.568 (–0.789)	0.809 (0.799)
		SIC	2 (2)	1.025 (–0.789)	0.903 (0.783)
	In first difference	AIC	11 (11)	–2.229 (–4.196)	0.007 (0.000)
		SIC	5 (1)	–3.839 (–14.177)	0.000 (0.000)
$lnHEXP_t$	In level	AIC	7 (4)	4.116 (–3.297)	1.000 (0.002)
		SIC	2 (2)	2.905 (–3.796)	0.997 (0.000)
	In first difference	AIC	1 (6)	–19.398 (–10.615)	0.355 (0.000)
		SIC	1 (1)	–19.398 (–19.947)	0.000 (0.000)
$lnCPI_t$	In level	AIC	15 (15)	2.262 (–1.795)	0.987 (0.240)
		SIC	3 (2)	5.348 (–1.150)	1.000 (0.582)
	In first difference	AIC	14 (14)	–2.219 (–3.036)	0.007 (0.006)
		SIC	2 (2)	–6.997 (–8.339)	0.000 (0.000)
$MPrate_t$	In level	AIC	6 (6)	–1.183 (–2.458)	0.158 (0.045)
		SIC	4 (4)	–0.991 (–1.924)	0.237 (0.141)
	In first difference	AIC	5 (5)	–3.569 (–4.478)	0.000 (0.000)
		SIC	3 (3)	–4.666 (–5.764)	0.000 (0.000)
$ABSrate_t$	In level	AIC	8 (8)	–0.679 (–2.456)	0.374 (0.046)
		SIC	5 (4)	–0.985 (–3.424)	0.240 (0.001)
	In first difference	AIC	14 (14)	–0.075 (–2.986)	0.614 (0.007)
		SIC	14 (14)	–0.075 (–2.986)	0.624 (0.009)

Notes: The DF-GLS test by Elliot et al. (1996) was performed with the Stata code ersur (Otero and Baum, 2017). The test procedure was the same as for the ADFmax test: The test was performed for each variable at the level and in the first difference (which in the test result in general least squares demeaned and detrended time series, respectively (see Elliot et al., 1996; Otero & Baum, 2017). The test regressions with a constant and a constant plus trend (results in parentheses) were estimated and the number of lags in the test regressions was determined using the AIC and SIC information criteria. The last two columns show the test statistics and the p-value of the statistics.

Source: Own calculations.

The results of the lag order selection of the VAR model (1) are shown in the Appendix. As in Shi et al. (2020) and Baum et al. (2025), this optimal lag order is then used in all subsamples. Shi et al. (2020) apply Bayesian information criteria, Baum et al. (2025) opt for a parsimonious lag structure (m=2, i.e. the first two lags). In our case, AIC and FPE specify m=5, while HQIC and SBIC specify m=2. We follow the literature and choose m=2. This selection is also confirmed by a VAR model (1) with an included trend. Given the results of DF-GLS ADFmax, the lag in the VAR model (1) is adjusted, increased by 1, resulting in an LA-VAR model with the first three lags.

Table 5 contains the results of the Granger causality for the entire sample. This uses a Wald test to test whether a variable of interest does not Granger-cause (i.e. null hypothesis is no Granger causality) another variable of interest at any point in time in the sample (Baum et al., 2022), or more specifically, whether i) the economic activity (industrial production) is not Granger caused by a health care feature, i.e. the job absenteeism rate ($ABSrate_t \overset{GC}{\rightarrow} lnIP_t$), health expenditure ($lnHEXP_t \overset{GC}{\rightarrow} lnIP_t$) and health policy uncertainty ($HEPU_t \overset{GC}{\rightarrow} lnIP_t$); ii) health outcomes (the absenteeism rate) are not Granger caused by industrial production ($lnIP_t \overset{GC}{\rightarrow} ABSrate_t$), health expenditures ($lnHEXP_t \overset{GC}{\rightarrow} ABSrate_t$), and health policy uncertainty ($HEPU_t \overset{GC}{\rightarrow} ABSrate_t$); iii) the health expenditures is not Granger caused by industrial production ($lnIP_t \overset{GC}{\rightarrow} lnHEXP_t$), the absence rate ($ABSrate_t \overset{GC}{\rightarrow} lnHEXP_t$), and the health policy uncertainty ($HEPU_t \overset{GC}{\rightarrow} lnHEXP_t$); iv) the health policy uncertainty in not Granger caused by industrial production ($lnIP_t \overset{GC}{\rightarrow} HEPU_t$), the job absenteeism rate ($ABSrate_t \overset{GC}{\rightarrow} HEPU_t$), and health expenditures ($lnHEXP_t \overset{GC}{\rightarrow} HEPU_t$). The rejection of null hypothesis is an indication of Granger causality at some time in the sample (Baum et al., 2022). Following Baum et al. (2022) and Shi et al. (2018, 2020) the maximum Wald statistics are compared to 95th and 99th bootstrapped values of statistics to draw conclusions about the causality. Wald statistics can differ in size which is due to the different subsampling of the methods (Baum et al., 2025).

Table 5: The results of Granger causality test for the total sample

	Max Wald FE	Max Wald RO	Max Wald RE
$ABSrate_t \xrightarrow{GC} lnIP_t$	20.843 (14.854; 20.102)	9.947 (14.676; 20.897)	22.556 (15.579; 21.717)
$lnHEXP_t \xrightarrow{GC} lnIP_t$	119.377 (11.883; 18.043)	238.462 (11.625; 17.954)	379.277 (12.660; 18.152)
$HEPU_t \xrightarrow{GC} lnIP_t$	18.008 (10.888; 17.179)	20.368 (12.033; 17.367)	22.110 (12.212; 17.643)
$lnIP_t \xrightarrow{GC} ABSrate_t$	4.430 (13.253; 21.804)	8.466 (13.614; 23.761)	25.633 (14.374; 24.477)
$lnHEXP_t \xrightarrow{GC} ABSrate_t$	7.484 (11.944; 17.853)	13.160 (12.330; 19.124)	24.540 (12.485; 19.991)
$HEPU_t \xrightarrow{GC} ABSrate_t$	3.361 (11.257; 17.477)	14.963 (12.052; 17.861)	17.109 (12.721; 18.992)
$lnIP_t \xrightarrow{GC} lnHEXP_t$	16.513 (11.991; 20.319)	17.265 (12.772; 20.844)	20.202 (13.171; 21.006)
$ABSrate_t \xrightarrow{GC} lnHEXP_t$	4.121 (10.122; 17.045)	11.656 (11.127; 17.562)	17.424 (11.774; 19.838)
$HEPU_t \xrightarrow{GC} lnHEXP_t$	14.108 (9.931; 16.992)	17.731 (11.184; 17.828)	17.731 (12.249; 18.083)
$lnIP_t \xrightarrow{GC} HEPU_t$	17.606	19.667	22.077

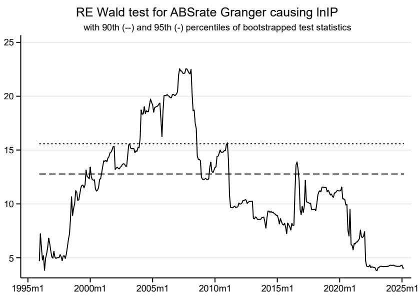
	(9.853; 16.432)	(10.800; 16.211)	(11.473; 16.605)
$ABSrate_t \overset{GC}{\rightarrow} HEPU_t$	2.039 (11.582; 17.205)	10.072 (12.796; 18.237)	10.638 (13.317; 19.375)
$lnHEXP_t \overset{GC}{\rightarrow} HEPU_t$	60.329 (10.654; 14.711)	46.701 (11.878; 14.858)	72.447 (12.387; 15.799)

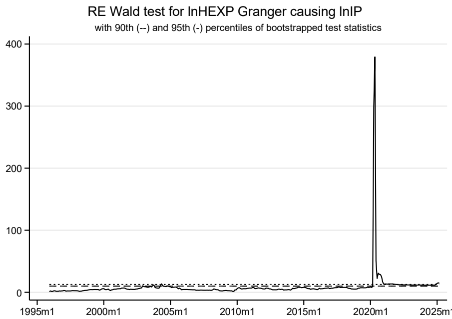
Notes: The maximum Wald test statistics for FE, RO and RE methods are reporter for the null hypothesis of no Granger causality for model (1). The 95th (the first value) and 99th percentiles (the second value) of the critical levels for the bootstrapped test statistics are given in parentheses. The results are calculated using the tvgc Stata code from Baum et al. (2022).

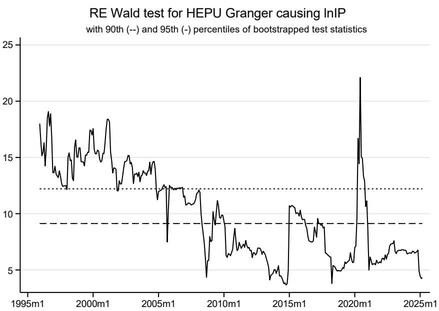
Source: Own calculations.

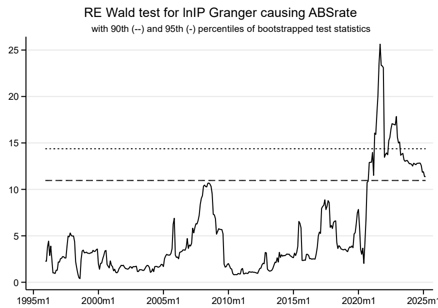
Above all, the results show that reverse causality can be identified between the variables of interest, regardless of the method used. For example, $lnHEXP_t$ is Granger causing $lnIP_t$, and conversely, the latter is Granger causing the former variable. For some pairs of variables, the results depend on the method chosen. For example, $ABSrate_t$ is Granger causing $lnIP_t$ at 5 % significance level, except for the RO method. The feedback causality, $lnIP_t$ Granger causing $ABSrate_t$, is identified only with RO method. No feedback can be identified also between $ABSrate_t$ and $HEPU_t$: $HEPU_t$ is Granger causing $ABSrate_t$ but not vice versa.
The Granger causality relationship between the variables may be limited in time to only some subperiods, which is analysed below by the time-varying Granger causality tests. To save space, we only present the results for the RE method. According to Baum et al. (2025), the RE and RO methods have greater explanatory power than the FE method when analysing time-varying Granger causality, while Shi et al. (2018) find that the RE method performs best of the three methods.

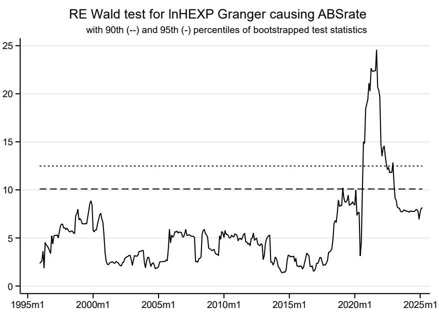
Figure 1: Time-varying RE Wald test results

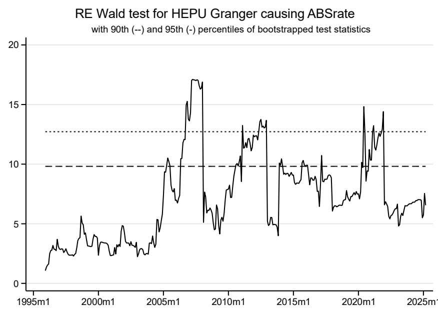

RE Wald test for ABSrate Granger causing lnIP
with 90th (--) and 95th (-) percentiles of bootstrapped test statistics

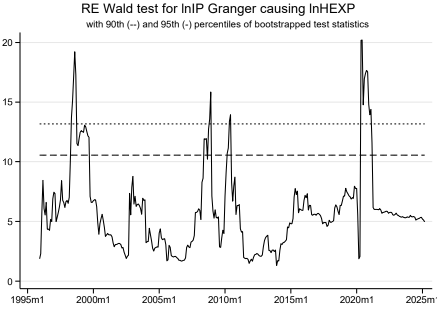

RE Wald test for lnHEXP Granger causing lnIP
with 90th (--) and 95th (-) percentiles of bootstrapped test statistics

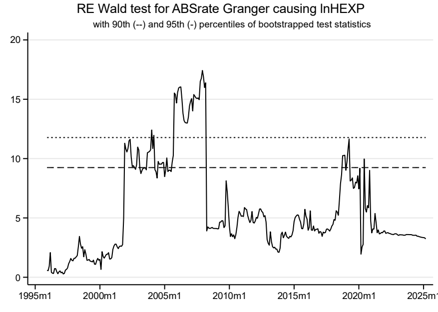

RE Wald test for HEPU Granger causing lnIP
with 90th (--) and 95th (-) percentiles of bootstrapped test statistics

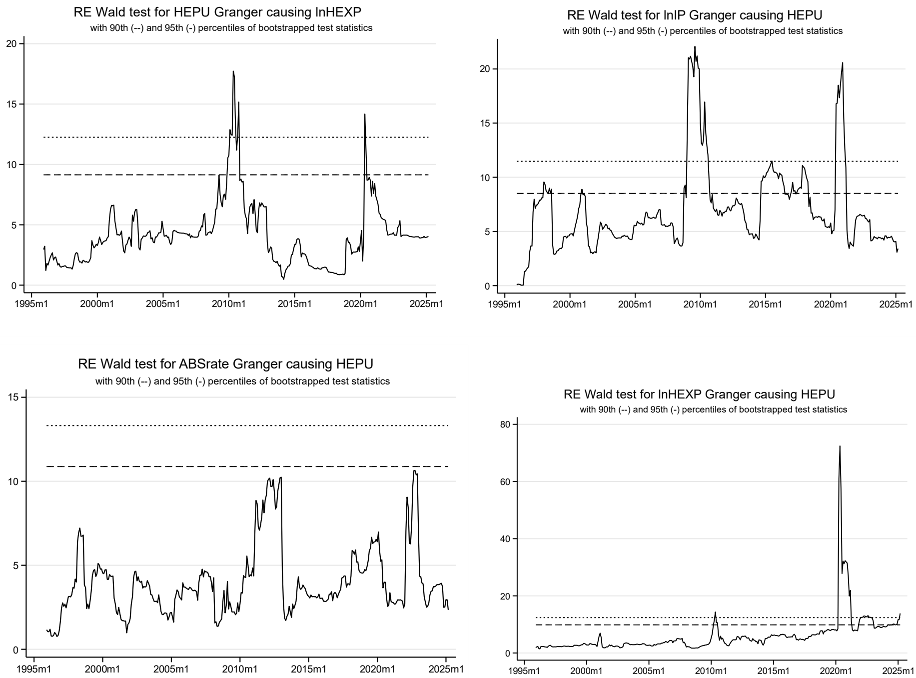

RE Wald test for lnIP Granger causing ABSrate
with 90th (--) and 95th (-) percentiles of bootstrapped test statistics


RE Wald test for lnHEXP Granger causing ABSrate
with 90th (--) and 95th (-) percentiles of bootstrapped test statistics


RE Wald test for HEPU Granger causing ABSrate
with 90th (--) and 95th (-) percentiles of bootstrapped test statistics


RE Wald test for lnIP Granger causing lnHEXP
with 90th (--) and 95th (-) percentiles of bootstrapped test statistics


RE Wald test for ABSrate Granger causing lnHEXP
with 90th (--) and 95th (-) percentiles of bootstrapped test statistics



Notes: Results of the time-varying Granger causality test based on model (1), with 90th and 95th percentiles of bootstrapped test statistics for the Wald test. The null hypothesis is that the first variable in the title of a specific graph does not Granger cause the second variable in the title of the graph. The test statistic exceeding the critical values leads to rejection of the null and conclusion that the first variable Granger causes the second variable. The Stata code tvgc from Baum et al. (2022) was used. The date on which the Wald test statistic exceeds the critical value is the start date for the rejection of the null hypothesis (Baum et al., 2018).

The results show that, with the exception of the period 2004–2008, the hypothesis of $ABSrate_t$ not Granger causing $lnIP_t$ can not be rejected at 5% significance level. We can also observe that $lnHEXP_t$ was Granger causing $lnIP_t$ from the second quarter of 2020 on, while $HEPU_t$ was Granger causing $lnIP_t$ in the first part of the observation period until around the end of 2004 and then in the last 3 quarters of 2020.

$ABSrate_t$ was Granger caused by $lnIP_t$ and $lnHEXP_t$ in the pandemic period and by $HEPU_t$ in 2007, occasionally in 2011–2012 and in the pandemic period.

$lnHEXP_t$ was Granger caused by $lnIP_t$ in the second half of 1998, in the second half of 2008, in the second quarter of 2010 and in 2020, by $ABSrate_t$ from the last quarter of 2005 to the end of the first quarter of 2008 and in the second quarter of 2019, and by $HEPU_t$ in 2010 and in the second quarter of 2020.

$HEPU_t$ was Granger caused by $lnIP_t$ in the period 2009–2010 and in 2020 and by $lnHEXP_t$ in the second quarter of 2010, 2020, 2022 and at the end of the observed period.

The results show that health care and economic activity are interrelated but this is time-dependent. In general, economic and health crises appear to increase this interrelation.

5 Discussion

The use of time-varying Granger causality is a promising approach for analysing the relationship between health care and the economy, as this study shows. The estimates suggest that in certain time periods workplace absenteeism, health expenditure, and health policy uncertainty Granger-cause industrial production. This means that changes in the health care sector can have an impact on the economy. This became clear at the beginning of the COVID-19 pandemic, when the number of COVID-19 cases increased, as did health-related workplace absenteeism (Groenewold et al., 2020), health expenditure (Vysochyna et al., 2023), and health policy uncertainty (Bloom et al., 2025). Although the increase in health care spending could not offset the negative impact of the COVID-19 epidemic on economic activity, it helped to mitigate its negative impact on the economy (Vysochyna et al., 2023).

6 Conclusion

The aim of this study was to analyse the relationship between health care and economic activity in the United States using time-varying Granger causality. The main finding is that there is a time-varying causal relationship between health care and economic activity, as observed during the COVID-19 epidemic. From a policy perspective, this indicates that growth in healthcare spending affects industrial production and vice versa. Policymakers should therefore promote growth in healthcare consumption and industrial production. This can be achieved in various ways, including fiscal measures. Growth in healthcare consumption can affect health outcomes, while improved population health can lead to higher productivity. Growth in healthcare expenditure can also be achieved through improved access to doctors (prevention) and health insurance, as well as by raising public awareness of the importance of health.

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Appendix

Table A.1: Lag selection results: a VAR model without trend

```
Time variable: time, 1990m1 to 2025m3
        Delta: 1 month

. varsoc HEPU lnIP lnHEXP lnCPI MPrate ABSrate, maxlag(12)

Lag-order selection criteria

   Sample: 1991m1 thru 2025m3                          Number of obs = 411
```

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-2160.79				.001529	10.544	10.5672	10.6027
1	2081.7	8485	36	0.000	2.0e-12	-9.92555	-9.7631	-9.5149
2	2294.95	426.5	36	0.000	8.3e-13	-10.7881	-10.4864*	-10.0254*
3	2340.58	91.258	36	0.000	7.9e-13	-10.8349	-10.394	-9.72029
4	2382	82.85	36	0.000	7.7e-13	-10.8613	-10.2811	-9.3947
5	2426.48	88.954	36	0.000	7.4e-13*	-10.9026*	-10.1832	-9.08395
6	2448.6	44.228	36	0.163	8.0e-13	-10.835	-9.97634	-8.66439
7	2473.07	48.951	36	0.073	8.4e-13	-10.7789	-9.78101	-8.25631
8	2492.7	39.25	36	0.326	9.2e-13	-10.6992	-9.56209	-7.82463
9	2528.26	71.129	36	0.000	9.2e-13	-10.6971	-9.42072	-7.47052
10	2569.53	82.534	36	0.000	9.0e-13	-10.7228	-9.30711	-7.14416
11	2613.14	87.226	36	0.000	8.7e-13	-10.7598	-9.20491	-6.82921
12	2641.08	55.888*	36	0.018	9.1e-13	-10.7206	-9.02646	-6.43802

```
   * optimal lag
   Endogenous: HEPU lnIP lnHEXP lnCPI MPrate ABSrate
    Exogenous: _cons
```

Source: Own calculations.

Table A.2: Lag selection results: a VAR model with a trend included

```
. varsoc HEPU lnIP lnHEXP lnCPI MPrate ABSrate, exog(trend) maxlag(12)
```

Lag-order selection criteria

Sample: 1991m1 thru 2025m3 Number of obs = 411

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1154.03				.000012	5.67413	5.72054	5.79146
1	2086.77	6481.6	36	0.000	2.0e-12	-9.92104	-9.73538	-9.45172
2	2299.29	425.02	36	0.000	8.4e-13	-10.78	-10.4551*	-9.95866*
3	2343.33	88.081	36	0.000	8.1e-13	-10.8191	-10.355	-9.64579
4	2383.98	81.317	36	0.000	7.9e-13	-10.8418	-10.2384	-9.31647
5	2427.94	87.913	36	0.000	7.6e-13*	-10.8805*	-10.1379	-9.00319
6	2449.88	43.875	36	0.172	8.1e-13	-10.8121	-9.93018	-8.58277
7	2474.39	49.017	36	0.073	8.6e-13	-10.7561	-9.73502	-8.17486
8	2494.13	39.489	36	0.317	9.4e-13	-10.677	-9.51667	-7.74376
9	2529.82	71.385	36	0.000	9.4e-13	-10.6755	-9.37593	-7.39027
10	2571.91	84.177	36	0.000	9.2e-13	-10.7052	-9.26631	-7.06791
11	2615.2	86.574	36	0.000	8.9e-13	-10.7406	-9.16253	-6.75137
12	2644.1	57.81*	36	0.012	9.2e-13	-10.7061	-8.98876	-6.36485

* optimal lag
Endogenous: HEPU lnIP lnHEXP lnCPI MPrate ABSrate
Exogenous: trend _cons

Povzetek članka v slovenskem jeziku (abstract in Slovene language)

Epidemija covida-19 je spodbudila potrebo po analizi razmerja med zdravstveno oskrbo in gospodarstvom. Ta članek analizira časovno spremenljivo razmerje med zdravstveno oskrbo in gospodarsko aktivnostjo v Združenih državah Amerike ter zapolnjuje vrzel v obstoječi literaturi. Z uporabo časovno spremenljive Grangerjeve vzročnosti raziskava ponuja empirične dokaze o časovno spremenljivem vzročnem razmerju med izdatki za zdravstvo in industrijsko proizvodnjo, kar ima pomembne posledice za oblikovanje politik.