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DOCUMENTO DE TRABAJO N° 373

Septiembre de 2025

Citar como:
Baioni, Tomás (2025). Analyzing the Short and Long-term Economic Impact of Natural Disasters at a Local Level: Evidence from Chile. Documento de trabajo RedNIE N°373.

Analyzing the short and long-term economic impact of natural disasters at a local level: evidence from Chile

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August 2025

Abstract

One of the salient aspects of climate change is the increment of both the intensity and frequency of natural disasters. This paper addresses how these factors interplay at a local level, focusing on Chilean regions at a quarterly basis for the period 2009-2025. To analyze intensity, I rely on the local projections method and find that on average, a 1% shock in natural disasters' intensity has an immediate negative effect in employment by 0.057%, and an immediate negative effect on the debt market, increasing the household debt by 0.123 p.p. Overall, my results suggest that a 1% shock in natural disasters' intensity has an immediate positive effect in real GDP by 0.015%, and a significant long-term negative effect on GDP by 0.054%, potentially showing signs of hysteresis. On the other hand, to analyze natural disasters' frequency, I rely on a local projections difference-in-differences (LP-DID) estimator and find that those Chilean regions that suffer a natural disaster, are more likely to experience short-term decreases in employment and GDP by 0.005% and 0.003%, respectively. I rely on a panel VAR model to estimate the impact of natural disasters' intensity as robustness checks, and find that my original conclusions hold: natural disasters have a short-term negative effect on employment at 0.005% and a long-term negative effect on growth at 0.170%.

Keywords— Climate change, natural disasters, environmental risks, emerging markets, local projections

JEL: C33, H70, Q54,

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1 Introduction

Global natural disasters have become more frequent and costly in recent years, driven primarily by climate change (USGCRP, 2017). Particularly, over 90 per cent of disasters are weather-related, including drought and aridification, wildfires, pollution and floods (UN 2023). Essentially, higher global surface temperatures increase the likelihood of droughts, affecting the hydrological cycle, which consequently increases the frequency of storms. As more water is evaporated into the atmosphere, more powerful storms develop. More heat in the atmosphere and warmer ocean surface temperatures lead to increased wind speeds in tropical storms, contributing to stronger disasters (USGS, 2021).

In light of this trend, it becomes increasingly important for policymakers to understand the short and long-term economic impacts of natural disasters. At a local or regional level, policymakers need to anticipate how these natural disasters will affect the economic growth, public revenue and expenditure, labour markets, investment and savings, etc, of their communities. At a national level, central banks need to incorporate the economic and social costs of natural disasters, to offset these external shocks using monetary policy (Keen & Pakko, 2011; Jawadi et al., 2024).

The literature on climate change and natural disasters, albeit relatively recent, is vast and diverse. Rasmussen, T. (2004) looks at the short and long-term effects of weather disasters in the Caribbean for the period 1970-2002 and finds that on average, natural disasters affect about 2 percent of a country's population each year and cause damage amounting to well over one-half of 1 percent of GDP, although the effect is more pronounced in developing countries, with the ECCU countries standing out as among the most vulnerable in the world in terms of the frequency of events.

Analogously, Fomby et al. (2011) analyze the yearly response of GDP growth to four types of natural disasters (droughts, floods, earthquakes, and storms) using a VAR-X model on a panel of 87 countries for the period 1960-2007, and find that natural disasters affect emerging economies proportionally more than developed countries.

Felbermayr & Gröschl (2014) rely on a dynamic regression model utilizing a database on natural disasters based on primary geophysical and meteorlogical sources, covering more than a hundred countries over the years 1979 to 2010, and find that A disaster in the top 1-percentile of the disaster index distribution reduces GDP per capita by at least 6.83%, with low and middle income countries experiencing the highest losses.

Recently, Fuje et al. (2023) analyze the macro-fiscal implications of droughts, storms, and floods, using ground and satellite disaster indicators spanning the past three decades across 164 countries, and find that within emerging and developing economies (EMDEs), a drought reduces output growth by 1.4 p.p. and government revenue by 0.7 % of GDP; whereas storms drag output growth in EMDEs, albeit with negligible impact on fiscal revenue; and limited impact of localized floods on growth and fiscal positions. In contrast, advanced economies (AEs) tend to experience negligible growth and fiscal consequences from climate-induced shocks.

Although the literature on natural disasters remains extensive, less has been focused on emerging markets, especially at a regional level. This paper addresses how these factors interplay at a local level, focusing on Chilean regions at a quarterly basis for the period 2009-2025. To analyze intensity, I rely on the local projections method and find that on average, a 1% shock in natural disasters' intensity has an immediate negative effect in employment by 0.057%, and an immediate negative effect on the debt market, increasing the household debt by 0.123 p.p. Overall, my results suggest that a 1% shock in natural disasters' intensity has an immediate positive effect in real GDP by 0.015%, and a significant long-term negative effect on GDP by 0.054%, potentially showing signs of hysteresis. On the other hand, to analyze natural disasters' frequency, I rely on a local projections difference-in-differences (LP-DID) estimator and find that those Chilean regions that suffer a natural disaster, are more likely to experience short-term decreases in employment and GDP by 0.005% and 0.003%, respectively. I rely on a panel VAR model to estimate the impact of natural disasters' intensity as robustness checks, and find that my original conclusions hold: natural disasters have a short-term negative effect on employment at 0.005% and a long-term negative effect on growth at 0.170%.

The contributions of this paper are simple but straightforward. To the best of my knowledge, this is the first work to analyze the economic impact of natural disasters at a regional level in emerging markets, differentiating between intensity and frequency. Moreover, this paper contributes to the literature of natural disasters, by estimating the effects on both short (within the first year) and medium-term (after one year) horizon, bridging the gap in the literature.

This paper is structured as follows. In section II, I develop a theory of economic recovery after weather disasters. In section III, I explain the data used in this paper; in section IV, I present the methodology utilized; in section V I present my main findings, differentiating between intensity and frequency. Finally in section VI, I present my conclusions and show some limitations and future projects related to this work.

2 A theory of economic recovery after natural disasters

In this section, I develop a theoretical framework following Hsiang & Jina (2014), to understand how rapid or strong the economic recovery is after a natural disaster, i.e., whether these shocks are meant to have persistent (hysteresis) or transitory effects (Field, 2012) (see Fig. 1). There exists four alternative scenarios:

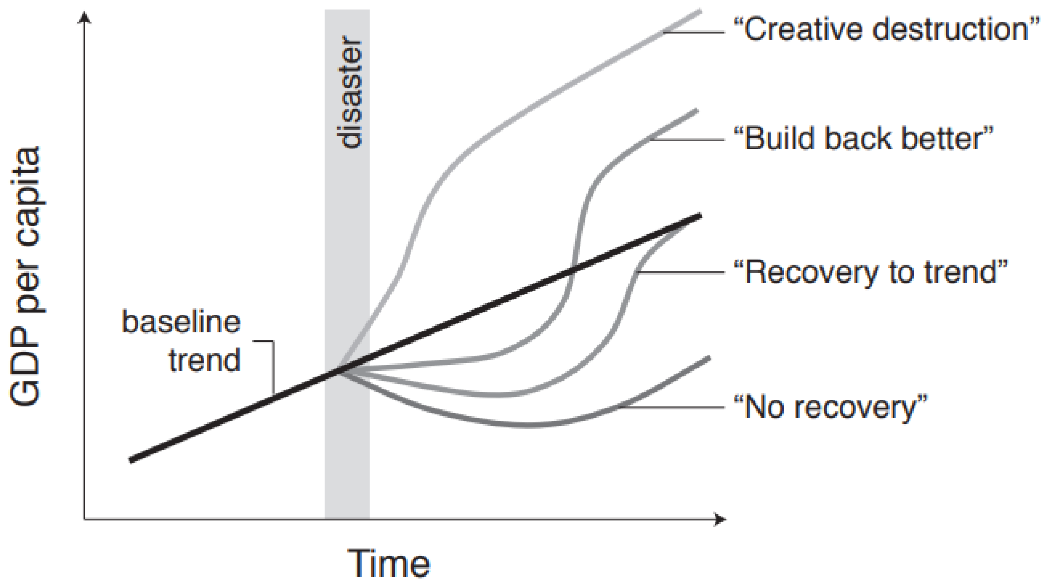
1. The "creative destruction" hypothesis argues that disasters have only a transitory effect in the economy, temporarily stimulating economies to grow faster, driven by higher demand for goods and services as people replace lost capital; or driven by international aid or assistance, increasing personal income levels and investment in the country. Evidence suggests that the construction sector, for example, exhibit short-term increases in production after these shocks (Belasen & Polachek, 2008; Hsiang, 2010; Deryugina, 2011).

2. The "build back better" hypothesis argues that growth may be affected initially, since human and fixed capital may be lost. However, the replacement of lost (old) assets with modern ones may have a positive long-run growth effect, driven by higher productivity (Cuaresma et al., 2008; Hallegatte & Dumas, 2009). The ultimate effect depends on whether this ex-post productivity gain after a disaster exceeds the productivity losses from the natural disaster.

3. The "recovery to trend" hypothesis argues that growth will be affected in a finite period, but that it rebounds thereafter, causing income levels to converge back to their pre-disaster trend, owing to an increment in the marginal product of capital as both K and L become relatively scarce after a disaster. Under the assumption of freely moving inputs, individuals and wealth migrate into devastated locations until output recovers to the pre-disaster trend (Yang (2008); Strobl (2011)). Evidence suggests that inflows of K are more common and rapid that inflows of L, as migration tends to be affected by these shocks (Yang, 2008; Smith et al., 2006; Strobl, 2011).

4. The "no recovery" (hysteresis) hypothesis argues that disasters negatively affect economic growth by destroying productive capital (machinery and equipment), labour capital (lives), durable and non-durable consumption goods (homes), generally replaced with funds that would otherwise be allocated to productive investments. Thus, the net effect translates into ex-post growth below pre-disaster trend, as the overall capital allocation is lower (Anttila-Hughes & Hsiang, 2011; Field et al., 2012).

Figure 1: Economic recovery after natural disasters following Hsiang & Jina (2014).



3 Data

3.1 Natural disasters database

Information on natural disasters come from the Emergency Events Database (EM-DAT), compiled by the Centre for Research on the Epidemiology of Disasters (CRED) at the Université Catholique de Louvain in Belgium. This comprehensive database provides information on the occurrence and effects of over 26,000 large-scale natural disasters across the world since 1900[1], at a regional level and with information of the date and severity of the impact. The EM-DAT includes natural disasters that check at least one of the following criteria: (i) 10 or more people dead; (ii) 100 or more people affected; the declaration of a state of emergency; and (iii) a call for international assistance.

In this work, I will include only weather-related natural disasters, including floods, storms, droughts, extreme temperature, earthquakes, landslides, wildfires and volcanic activity [2]. It is worth noting that the EM-DAT defines floods as "a general term for the overflow of water from a stream channel onto normally dry land in the floodplain (riverine flooding), higher-than-normal levels along the coast (coastal flooding) and in lakes or reservoirs as well as ponding of water at or near the point where the rain fell (flash floods)"; storms as "meteorological events including extra-tropical, tropical and convective storms"; droughts as "an extended period of unusually low precipitation that produces a shortage of water for people, animals and plants", extreme temperatures as "a general term for

1. Although it is suggested to utilize disasters' data from 2000 onwards to avoid biases and information errors.
2. I exclude epidemic episodes.

temperature variations above (extreme heat) or below (extreme cold) normal conditions"; earthquakes as "sudden movements of a block of the Earth's crust along a geological fault and associated ground shaking"; a landslide as "any kind of moderate to rapid soil movement including lahars, mudslides, and debris flows (under dry conditions)"; wildfires as "any uncontrolled and non-prescribed combustion or burning of plants in a natural setting such as a forest, grassland, brush land or tundra, which consumes natural fuels and spreads based on environmental conditions"; and finally, volcanic activity as "a type of volcanic event near an opening/vent in the Earth's surface including volcanic eruptions of lava, ash, hot vapor, gas, and pyroclastic material".

3.2 Chile's regional economic database

For Chilean regional economic data, I rely on the Central Bank of Chile's database for the majority of the series. The primary outcome of interest includes real GDP by region, proxying income levels; debt (defined as the average between commercial, consumption and household debt), used to proxy leverage of the economy; and employment levels, and the unemployment rate, proxying the labour market to analyze labour transitions across regions. Moreover, for data on hydrocarbon prices (defined as the average of gasoline, diesel, and end-user LNG), I rely on the Chilean Ministry of Energy database, to proxy for energy inflation. Data is expressed at a quarterly basis for the period 2009-2025, owing to data availability. A summary can be found in Table 1 (see Table 1).

Table 1: Data coverage and sources of variables included in the model

Variable	**Horizon**	**Source**
Real GDP	Q1 2009-Q1 2025	Central Bank of Chile
Hydrocarbon prices (in US dollars)	Q1 2009-Q1 2025	Chile's Ministry of Energy
People employed (in thousands)	Q1 2010-Q1 2025	Central Bank of Chile
Unemployment rate (in %)	Q1 2010-Q1 2025	Central Bank of Chile
Debt (in %)	Q1 2009-Q1 2025	Central Bank of Chile

4 Methodology

As already highlighted, this paper seeks to estimate how intensity and frequency of natural disasters, interplay in the economy at a regional level. For the former goal, I use the local projections method developed in Jordà (2005), as it is found to be more robust to misspecification and non-linearities (Olea-Montiel & Plagborg-Møller, 2021). In the baseline specification, following Roth Tran et al. (2024) and Costa & Hooley (2025), I estimate the following equation:

$$y_{c,t+h} - y_{c,t-1} = \alpha^h + \beta^h DI_{c,t} + \gamma^h X_{c,t} + \omega^h_{r(c),t} + \mu_{c,t+h} \tag{1}$$

where h=0, 1... 16 quarters (or up until 4 years after the impact), $y_{c,t}$ the variable of interest in region c at time t, β^h the response of the variable of interest to the natural disaster's intensity (in this case, the cumulative impact), $X_{c,t}$ a set of control variables and $\omega^h_{r(c),t}$ region and time fixed effects. The key assumption in equation (1) is that the disaster indicator is orthogonal to the error term $\mu_{c,t+h}$, this is, that the EM-DAT disaster declarations are exogenous with respect to any factors affecting the dependent variables that are unobserved or omitted from the model.

I define the variable DI as:

$$DIc,t = \frac{killed_{c,t} + 0.3 * affected_{c,t}}{population_{c,t}} \tag{2}$$

where killed and affected represents number of people killed and affected, respectively, in the natural disaster; and population the total number of people in the region at the time of the disaster. As opposed to Fomby et al. (2011), I treat the intensity variable as a continuous variable instead of a dummy, thus incorporating low intensity natural disasters to the estimate.

For frequency, I rely on a local projections difference-in-differences (lpdid) model developed in Dube et al. (2023), to recover the average treatment effect, as it is found to work well in the so-called repeated "one-off" treatments in which treatment is by definition confined to a single period, even though its effects may be dynamic and persistent over time, such as in the case of natural disasters. Particularly, I estimate the following equation:

$$y_{c,t+h} - y_{c,t-1} = \alpha^h + \delta^h DD_{c,t} + \gamma^h X_{c,t} + \omega^h_{r(c),t} + \mu_{c,t+h} \tag{3}$$

where DD is a dummy that takes the value of 1 if a region c suffered a disaster at time t, and 0 otherwise. δ^h in each regression is the event study estimate for event-time h, while averaging δ^h over the post-treatment periods gives an estimate of the average treatment effect.

In both models, I include as controls, debt, the unemployment rate, hydrocarbon prices, a recession dummy that takes the value of 1 if Chile experienced a recession in period t and 0 otherwise, to account for national spillovers, as well as the forward shocks of the natural disasters variable, to solve for misspecification, following Beirne et al. (2025)[3]. All variables are transformed into their logarithms (except debt and the unemployment rate), and then into their first differences to account for stationarity, so the estimated effects are shown as percentages or percentages points for the effect on the unemployment rate and debt. Moreover, 4 lags are included to control for autocorrelation, accounting for yearly effects[4]. I test as well the models using 2 and 6 lags as sensitivity analysis and find no significant changes in the results (see Fig. 5 and 6 in the Appendix).

5 Results

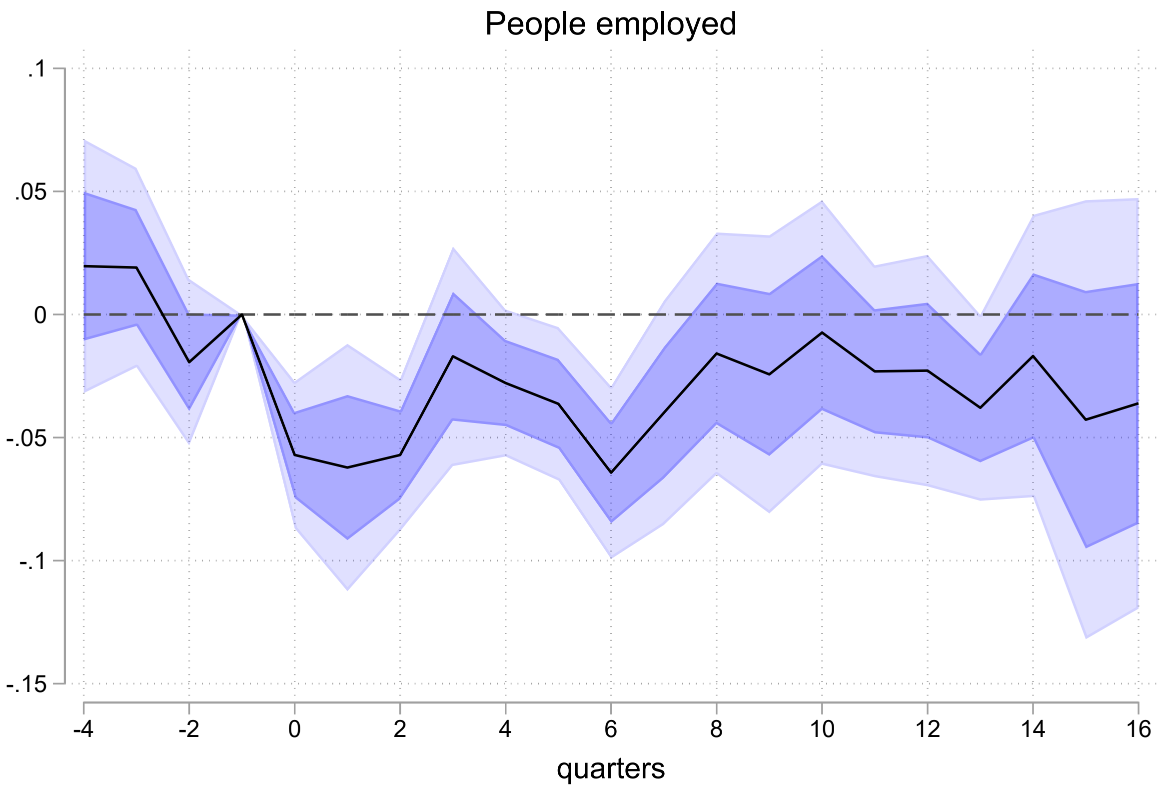
5.1 Natural disasters' intensity

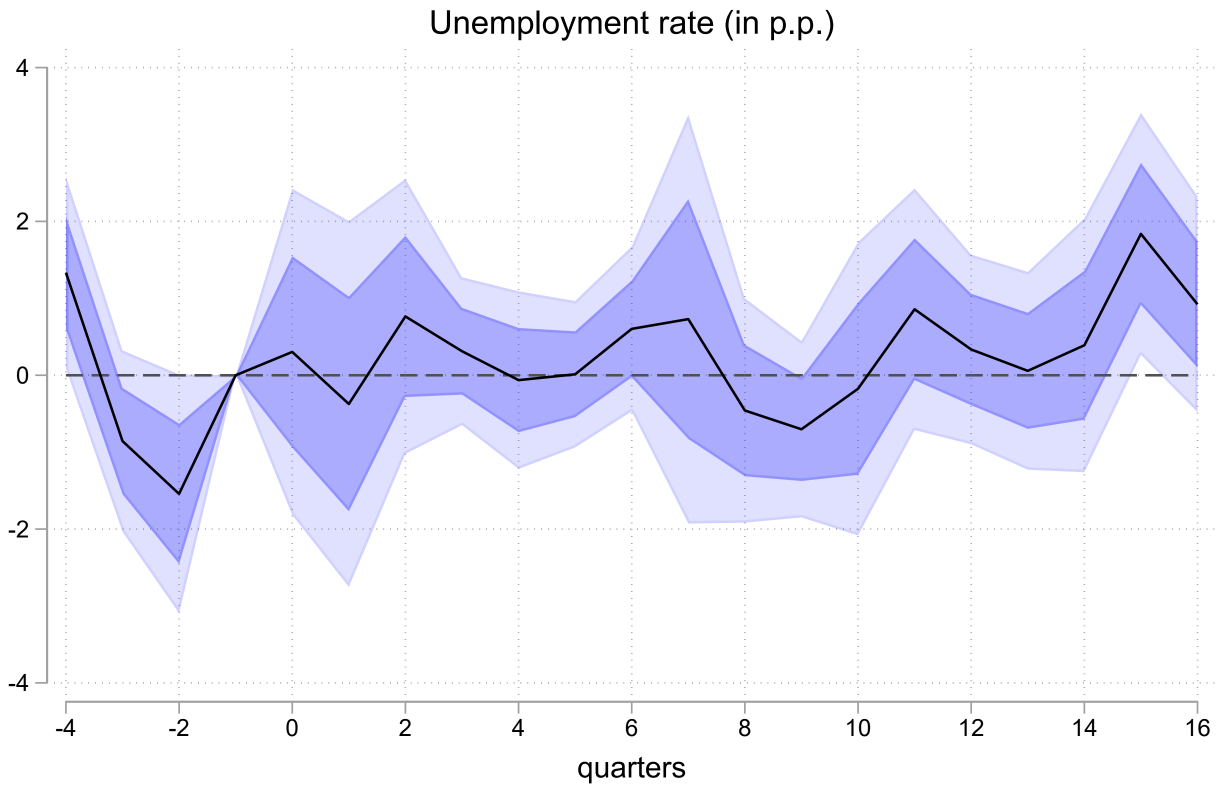
To begin with, I present the impulse response functions estimates based on natural disasters' intensity. Results suggest that on average, a 1% shock in natural disasters' intensity has an immediate negative effect in the labour market, as the people employed fall by 0.06% in the same quarter of the natural disaster and remains negative thereafter. On the other hand, a natural disaster intensity shock does not seem to transmit directly to the unemployment rate immediately, significantly increasing it in the long-term by a cumulative 1.7 p.p. When looking at hydrocarbon prices, only liquified natural gas prices immediately increase after the shock. When observing the debt market, estimates suggest that household debt increases immediately by 0.1 p.p, whereas consumption debt decreases by 0.3 p.p., showing signs of potential reallocation of disposable income, thus affecting households' leverage. .Overall, my results suggest that a 1% shock in natural disasters' intensity has an immediate positive effect on GDP by 0.02%. Then, the effect remains negative after 2 years, becoming statistically significant in the long run by an accumulated 0.05%. This is, my estimates suggest a potential "creative destruction" effect immediately, with government expenditure offseting the negative effects of these shocks, but a long-run "no-recovery" effect, with growth remaining below pre-disaster trend (see Fig. 2).

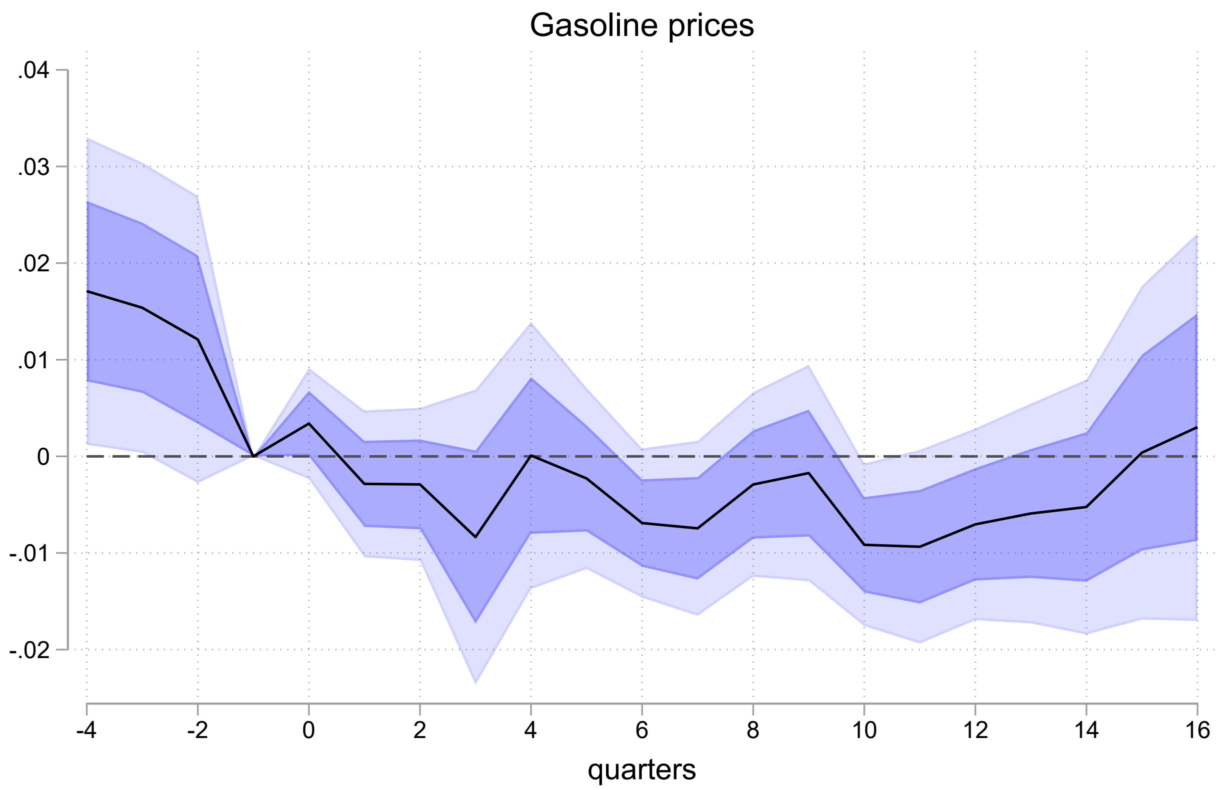
3. The idea is that if natural disasters' shocks negatively impact the economy, then future shocks may also impact the economy at future periods.

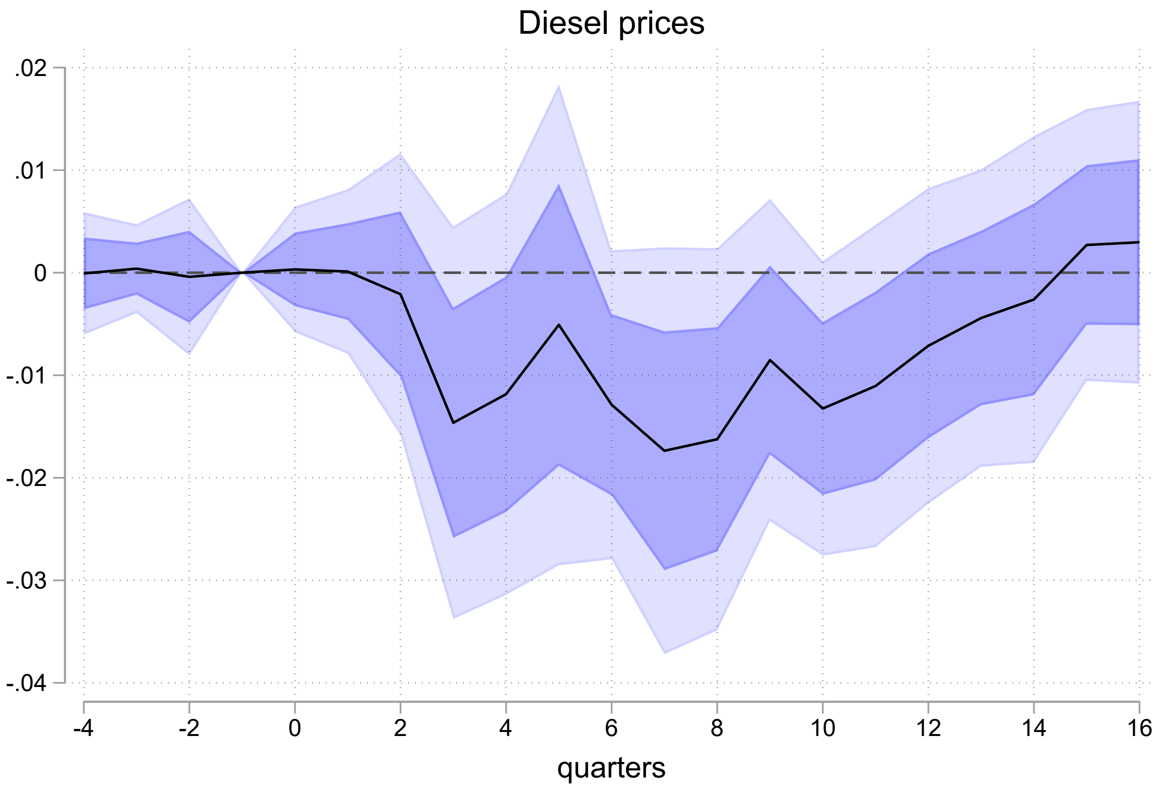
4. Real GDP is smoothed out with a 4-period moving average to adjust for seasonality.

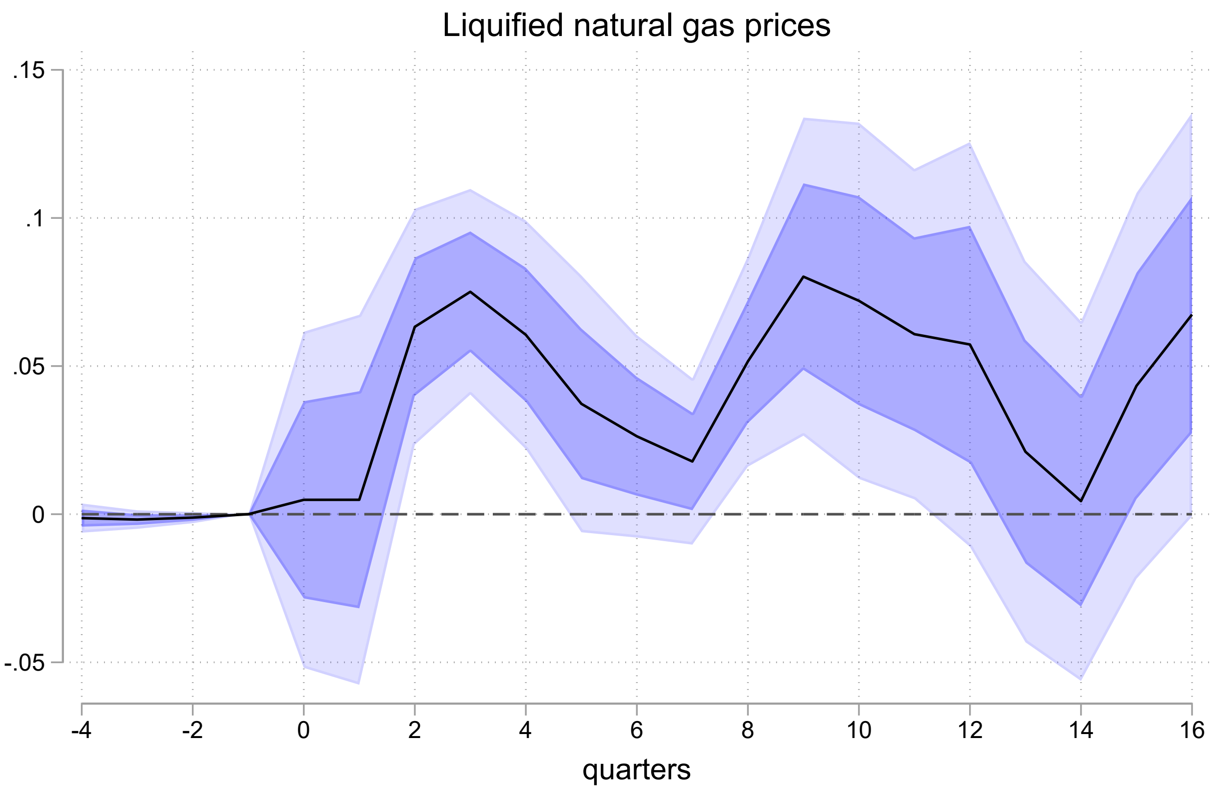
Figure 2: Impulse response functions from a 1% natural disasters' intensity shock

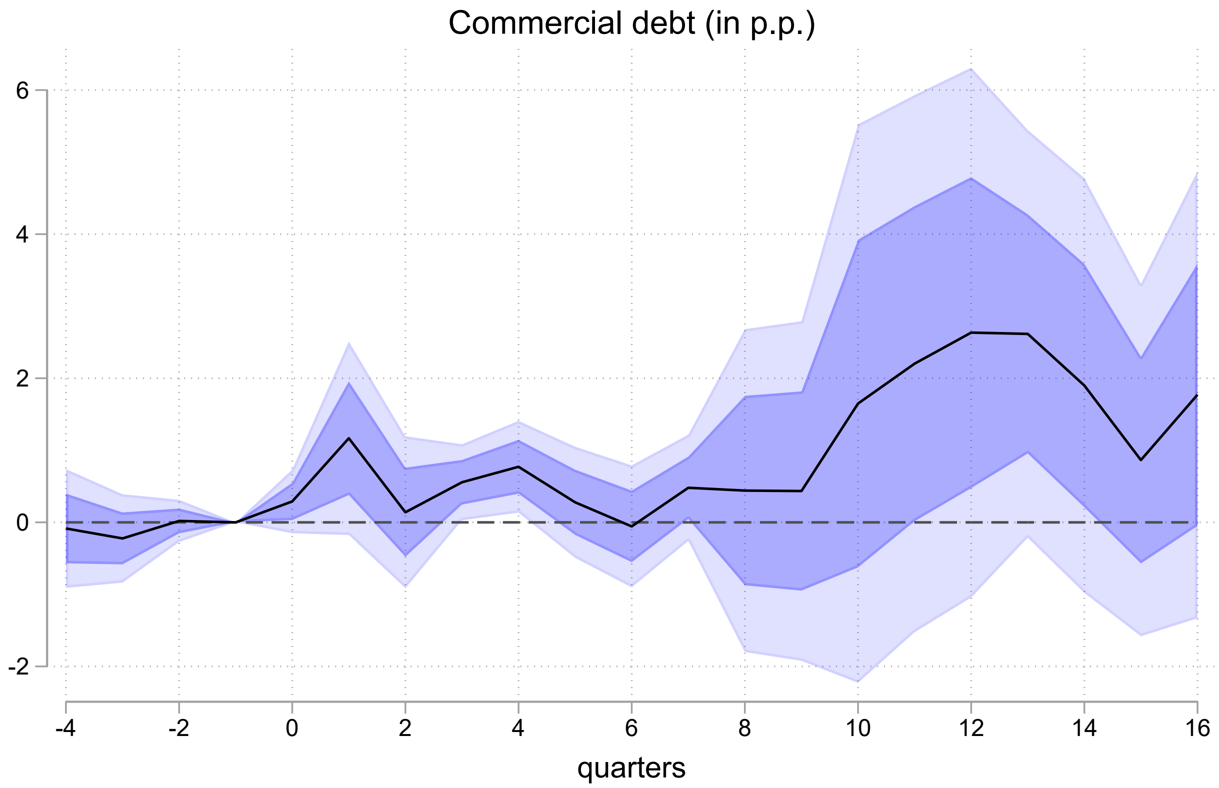


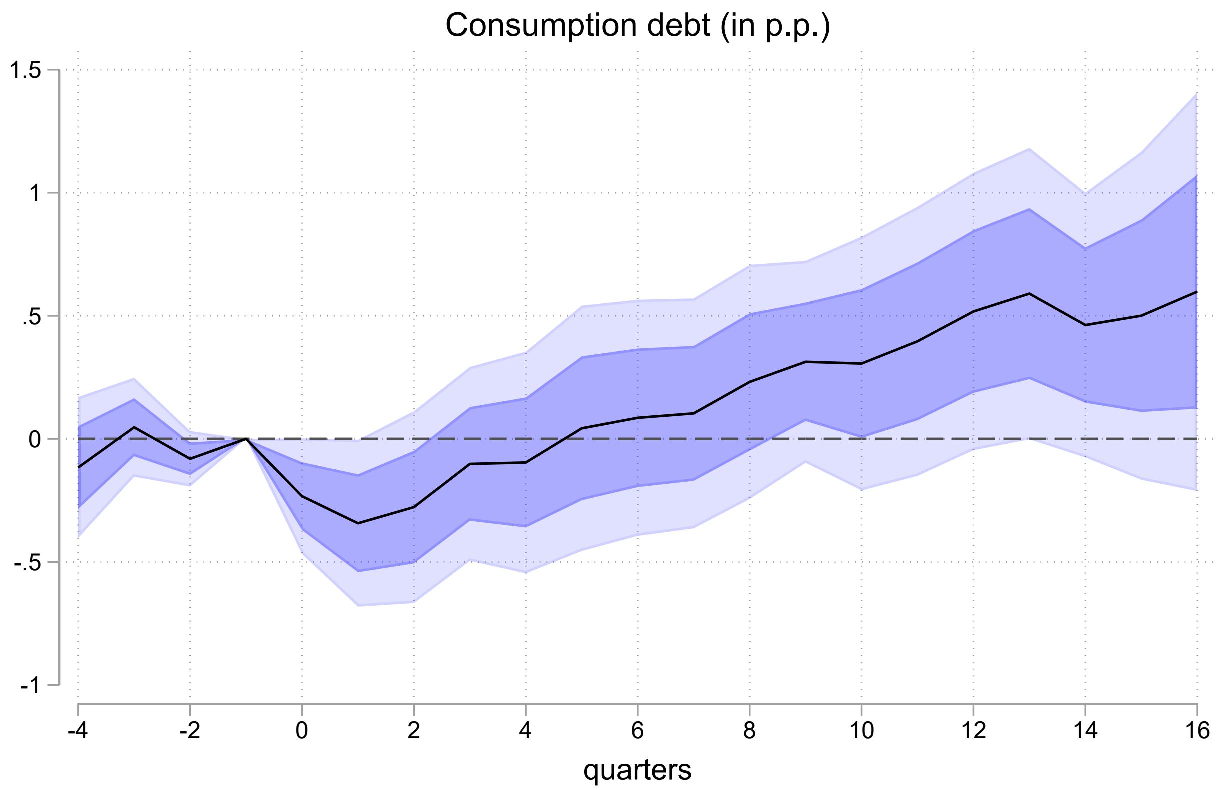

Unemployment rate (in p.p.)
4
2
0
-2
-4
-4
-2
0
2
4
6
8
10
12
14
16
quarters

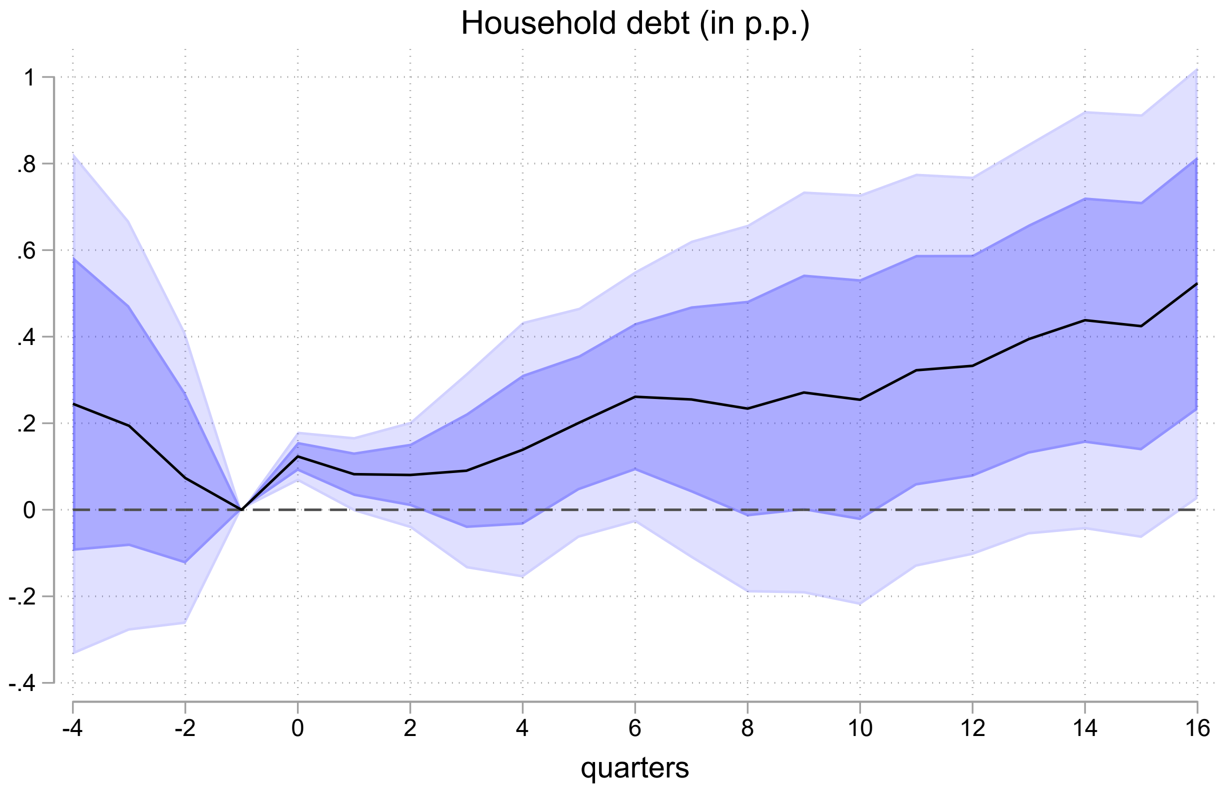

Gasoline prices
.04
.03
.02
.01
0
-.01
-.02
-4
-2
0
2
4
6
8
10
12
14
16
quarters

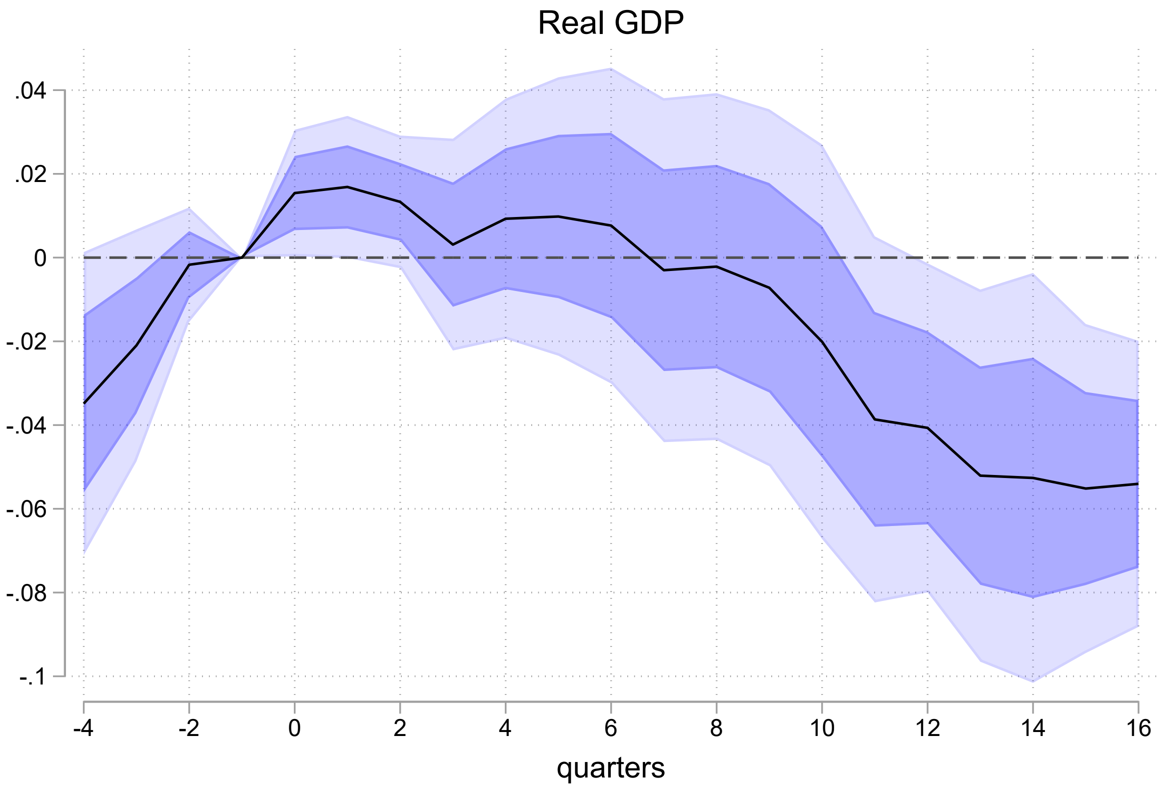

Diesel prices
.02
.01
0
-.01
-.02
-.03
-.04
-4
-2
0
2
4
6
8
10
12
14
16
quarters


Liquified natural gas prices
.15
.1
.05
0
-.05
-4
-2
0
2
4
6
8
10
12
14
16
quarters


Commercial debt (in p.p.)
6
4
2
0
-2
-4
-2
0
2
4
6
8
10
12
14
16
quarters


Consumption debt (in p.p.)
1.5
1
.5
0
-.5
-1
-4
-2
0
2
4
6
8
10
12
14
16
quarters


Household debt (in p.p.)
1
.8
.6
.4
.2
0
-.2
-.4
-4
-2
0
2
4
6
8
10
12
14
16
quarters

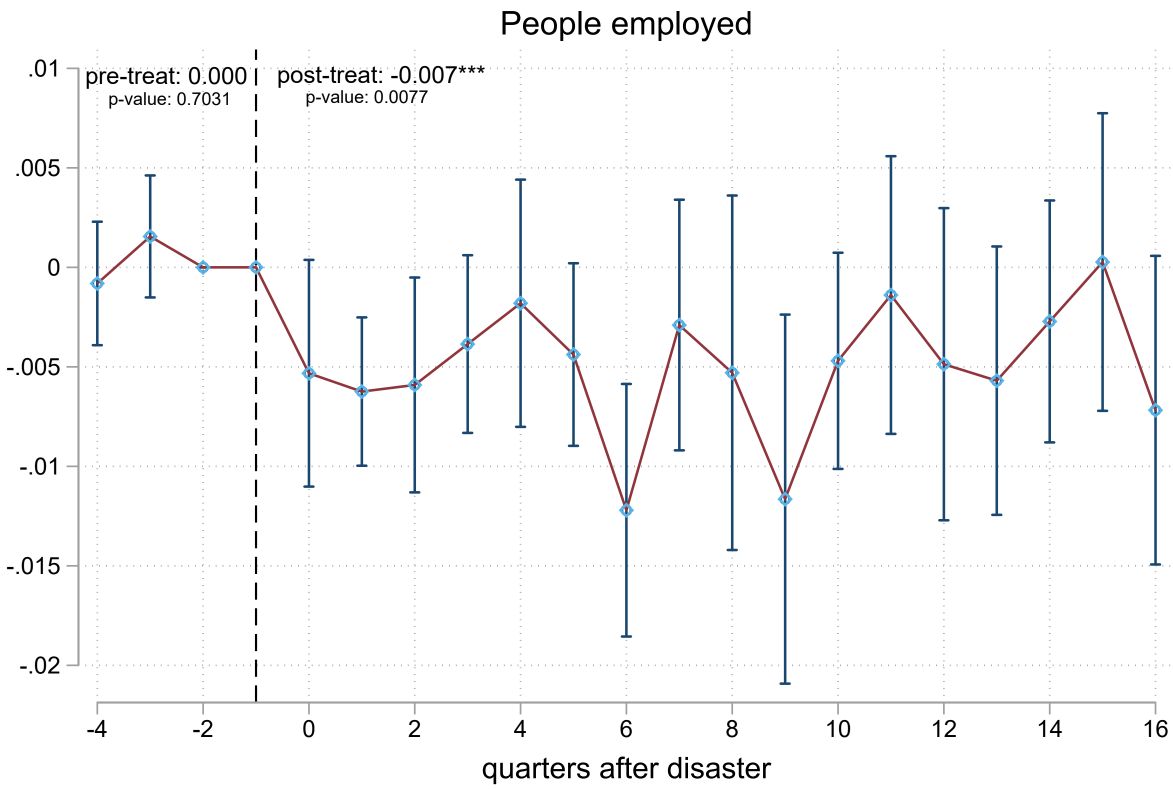


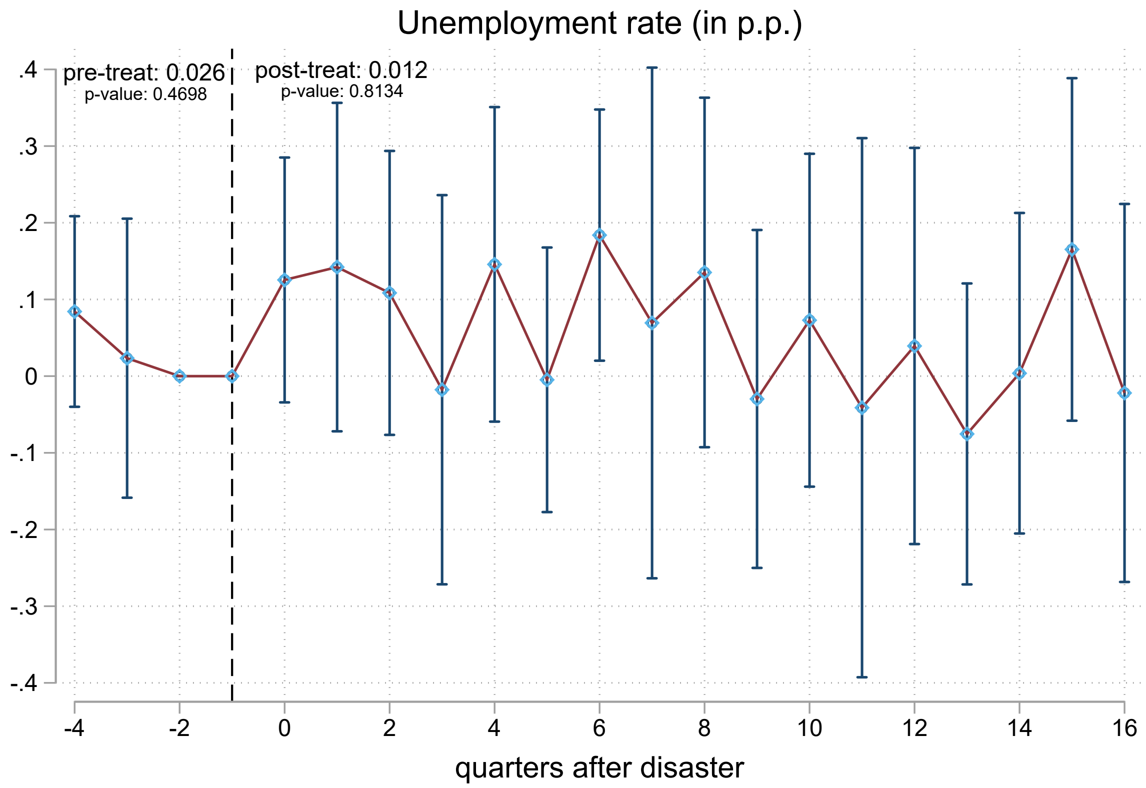
Note: shaded areas corresponds to 90 and 68% confidence bands.

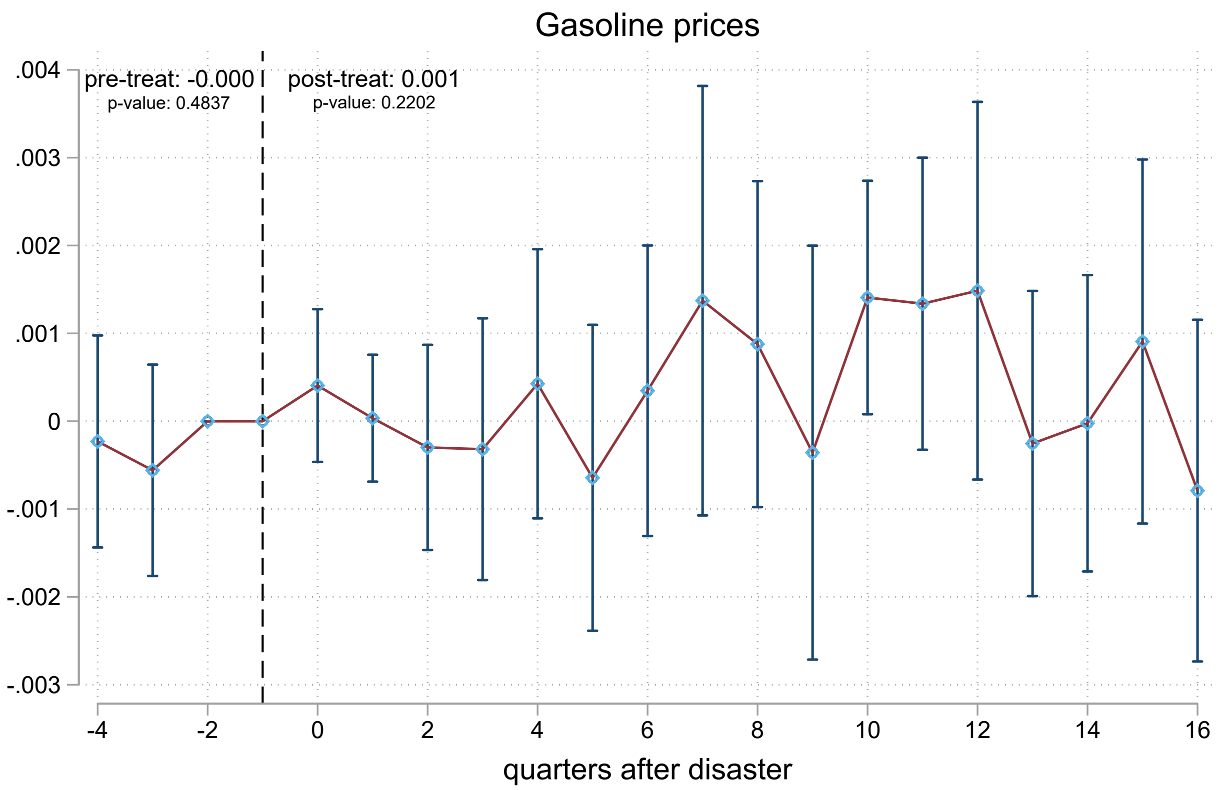
5.2 Natural disasters' frequency

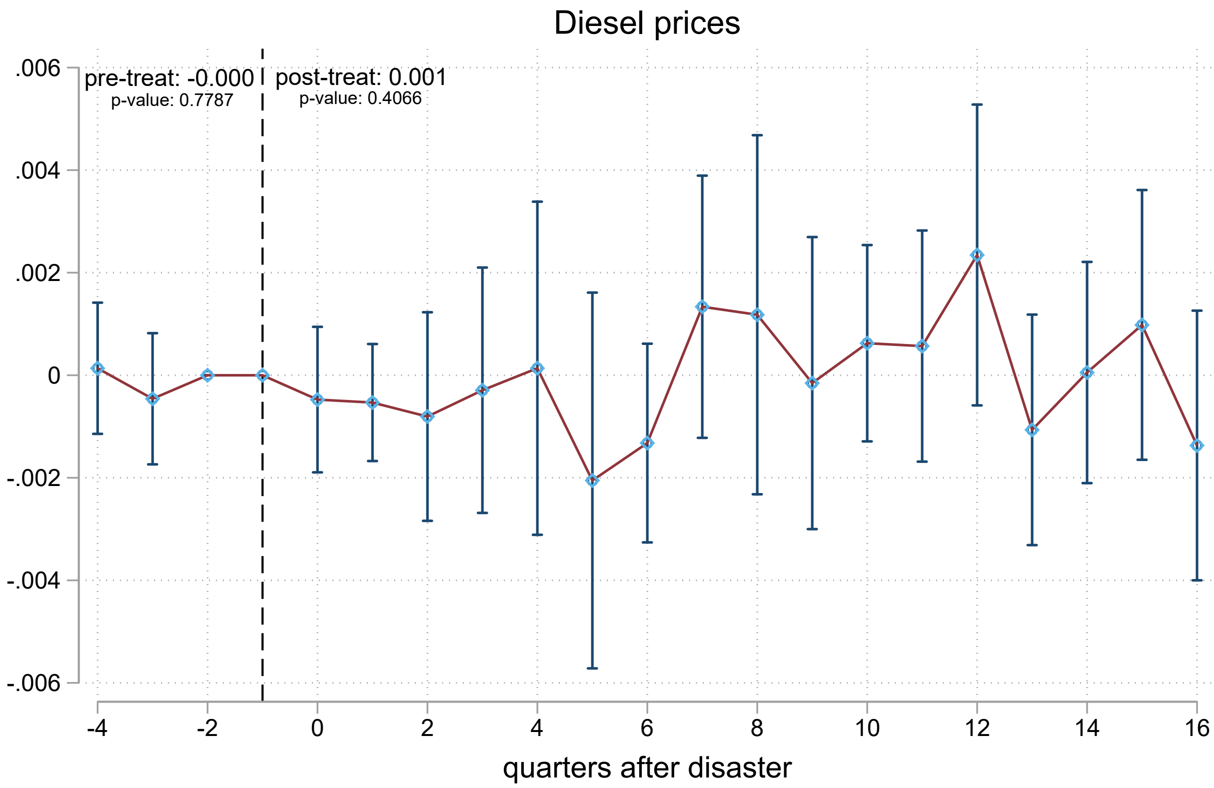
In this subsection, I move on to present the effects of natural disasters' frequency. Results suggest that on average, Chilean regions that suffer a natural disaster are more likely to experience lower immediate employment by 0.005% and higher unemployment rate, albeit the latter not statistically significant; higher hydrocarbon prices and debt, although not statistically significant; and lower immediate GDP by 0.003% (see Fig. 3).

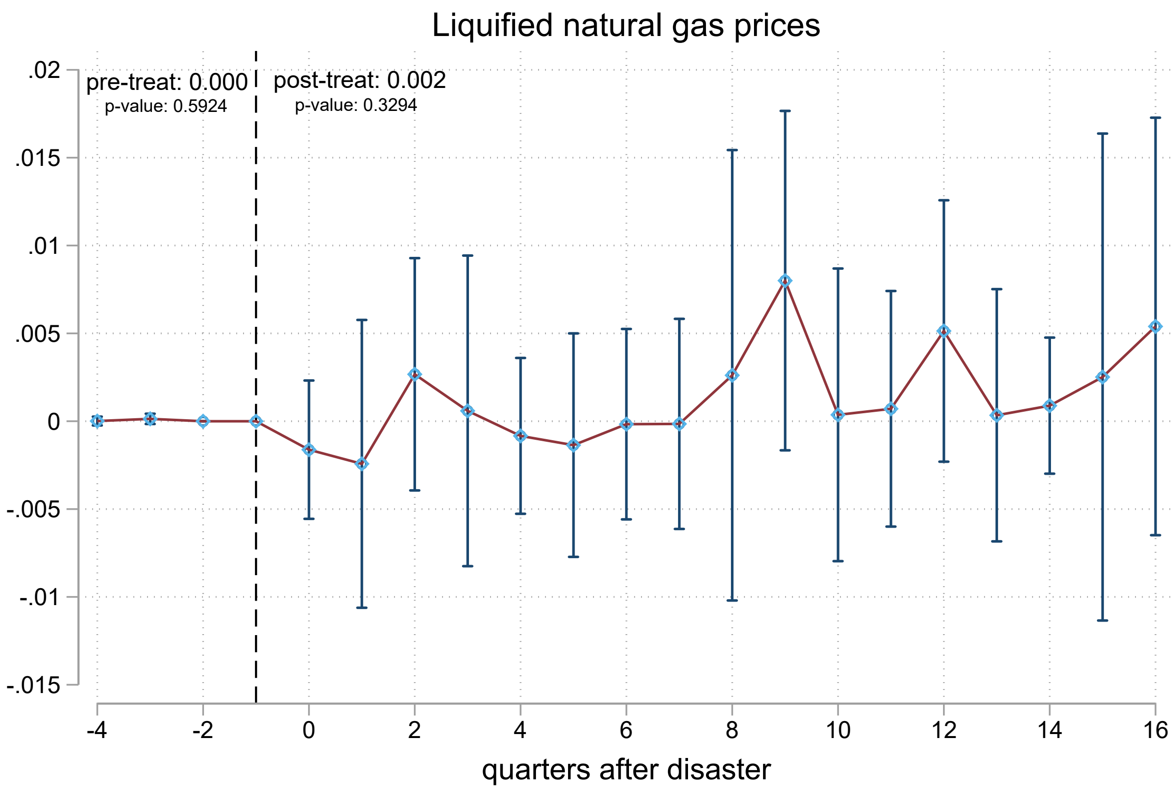
Figure 3: Average treatment effect from a natural disaster event

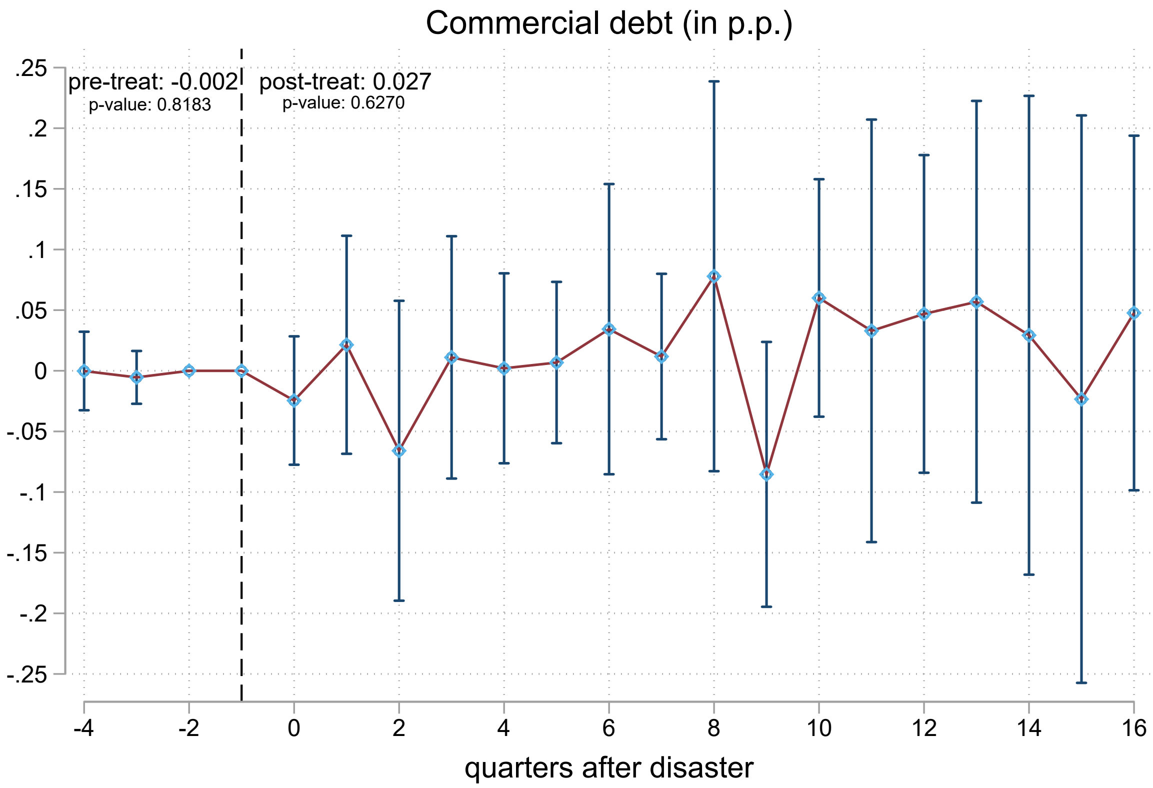


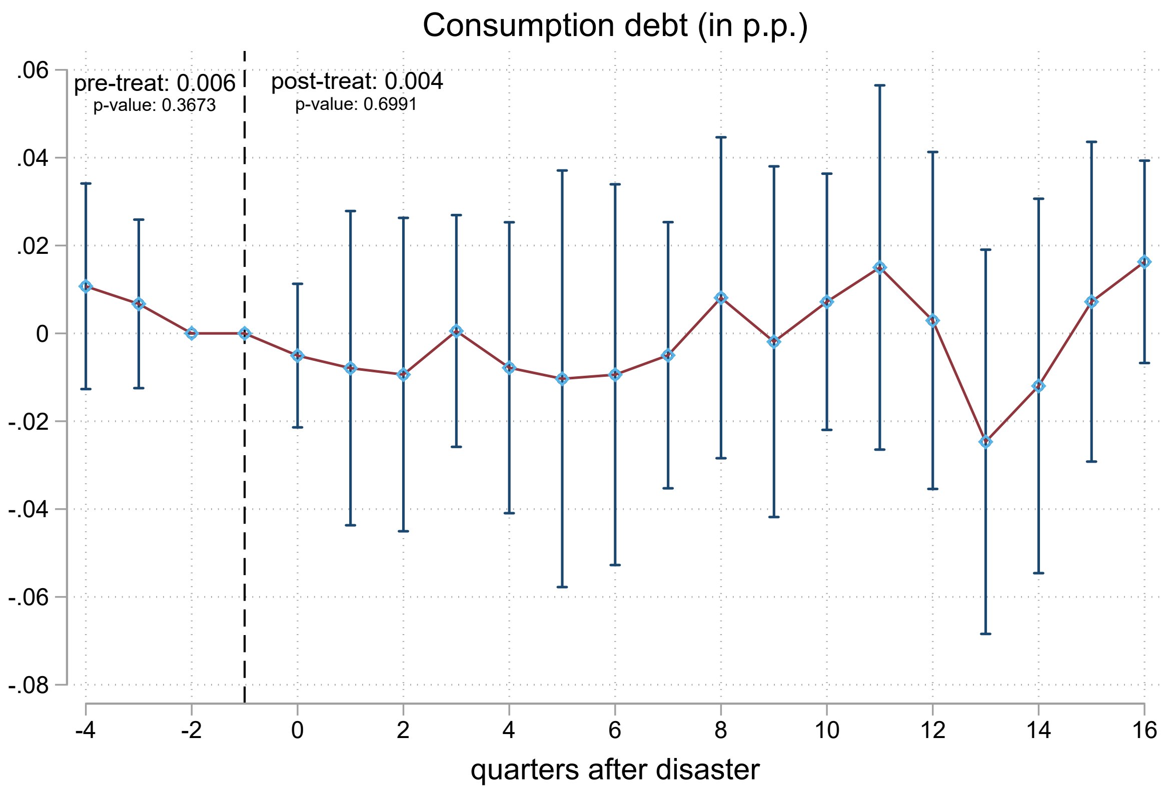

Unemployment rate (in p.p.)
pre-treat: 0.026
p-value: 0.4698
post-treat: 0.012
p-value: 0.8134
.4
.3
.2
.1
0
-.1
-.2
-.3
-.4
-4
-2
0
2
4
6
8
10
12
14
16
quarters after disaster

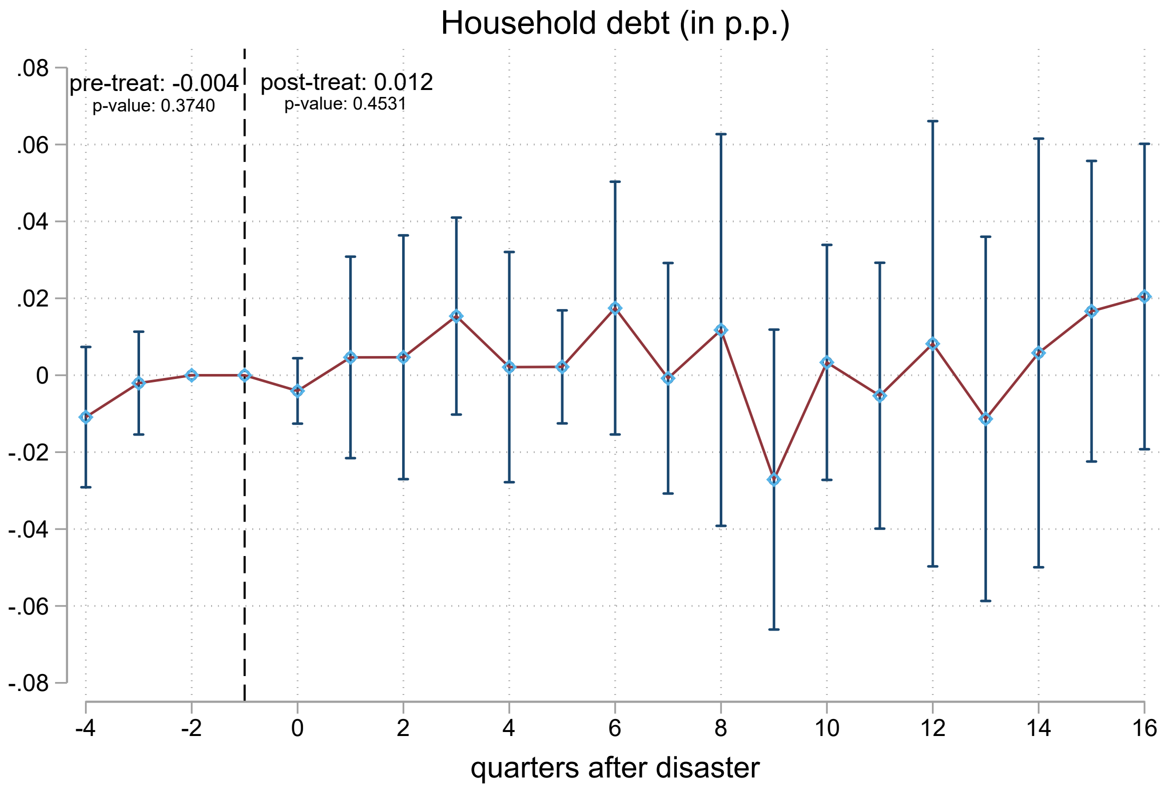

Gasoline prices
pre-treat: -0.000
p-value: 0.4837
post-treat: 0.001
p-value: 0.2202
.004
.003
.002
.001
0
-.001
-.002
-.003
-4
-2
0
2
4
6
8
10
12
14
16
quarters after disaster

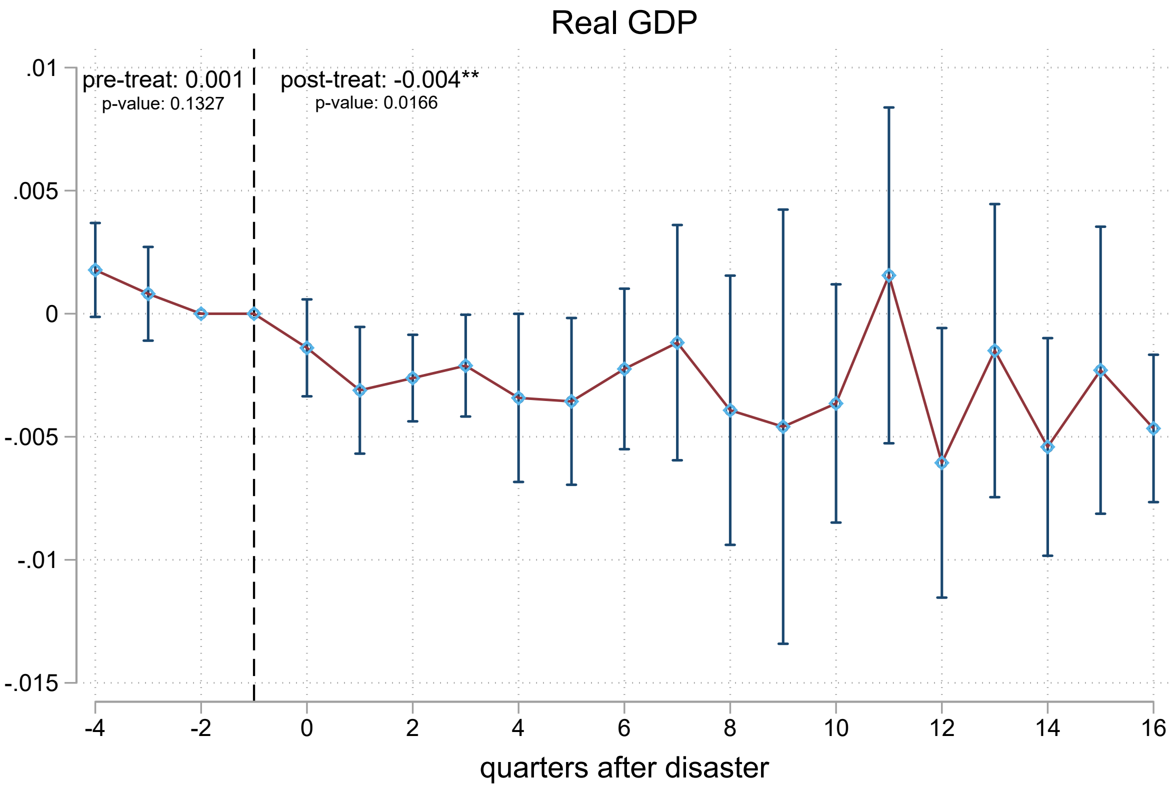

Diesel prices
pre-treat: -0.000
p-value: 0.7787
post-treat: 0.001
p-value: 0.4066
.006
.004
.002
0
-.002
-.004
-.006
-4
-2
0
2
4
6
8
10
12
14
16
quarters after disaster


Liquified natural gas prices
pre-treat: 0.000
p-value: 0.5924
post-treat: 0.002
p-value: 0.3294
.02
.015
.01
.005
0
-.005
-.01
-.015
-4
-2
0
2
4
6
8
10
12
14
16
quarters after disaster


Commercial debt (in p.p.)
pre-treat: -0.002
p-value: 0.8183
post-treat: 0.027
p-value: 0.6270
quarters after disaster


Consumption debt (in p.p.)
pre-treat: 0.006
p-value: 0.3673
post-treat: 0.004
p-value: 0.6991
quarters after disaster


Household debt (in p.p.)
pre-treat: -0.004
p-value: 0.3740
post-treat: 0.012
p-value: 0.4531
.08
.06
.04
.02
0
-.02
-.04
-.06
-.08
-4
-2
0
2
4
6
8
10
12
14
16
quarters after disaster

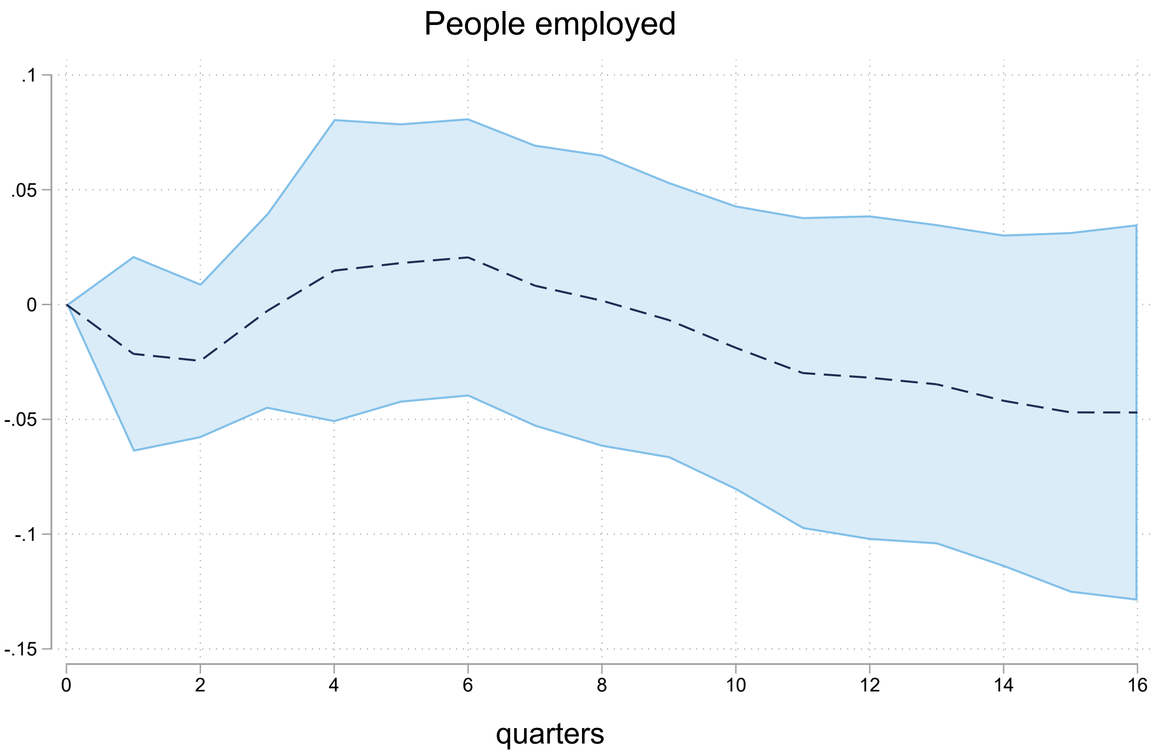


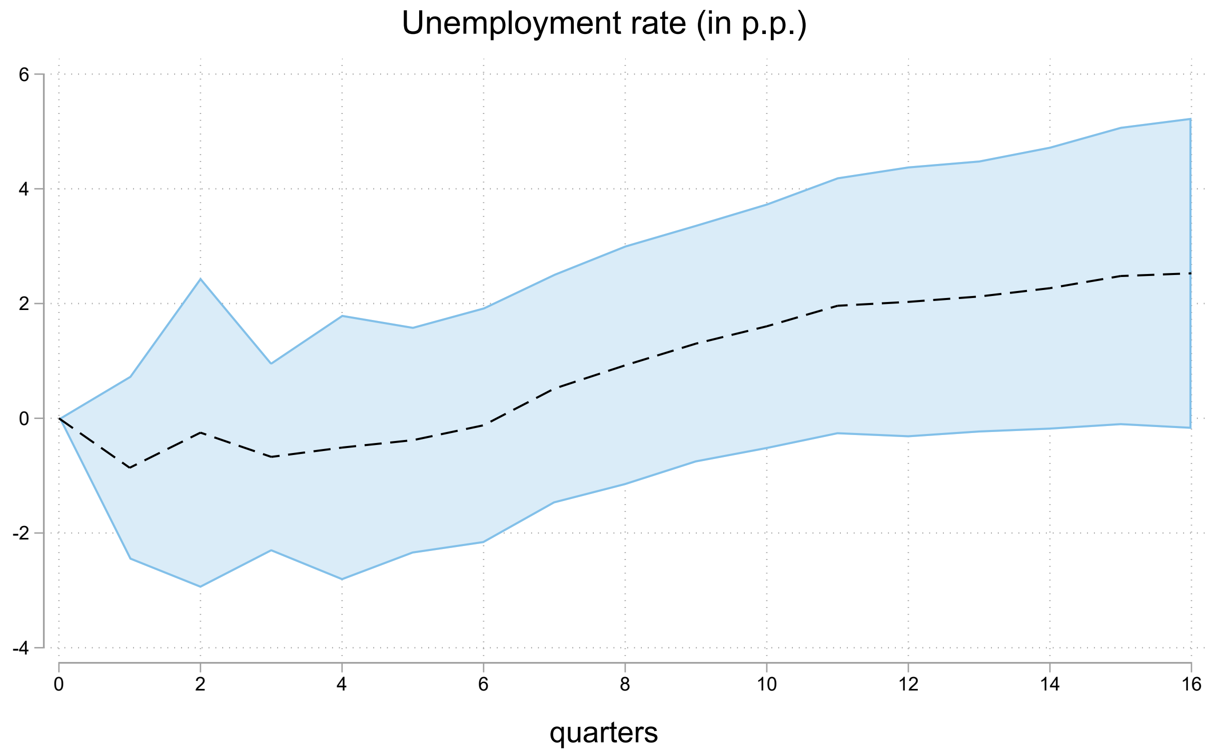
Note: shaded areas corresponds to 90 and 68% confidence bands.

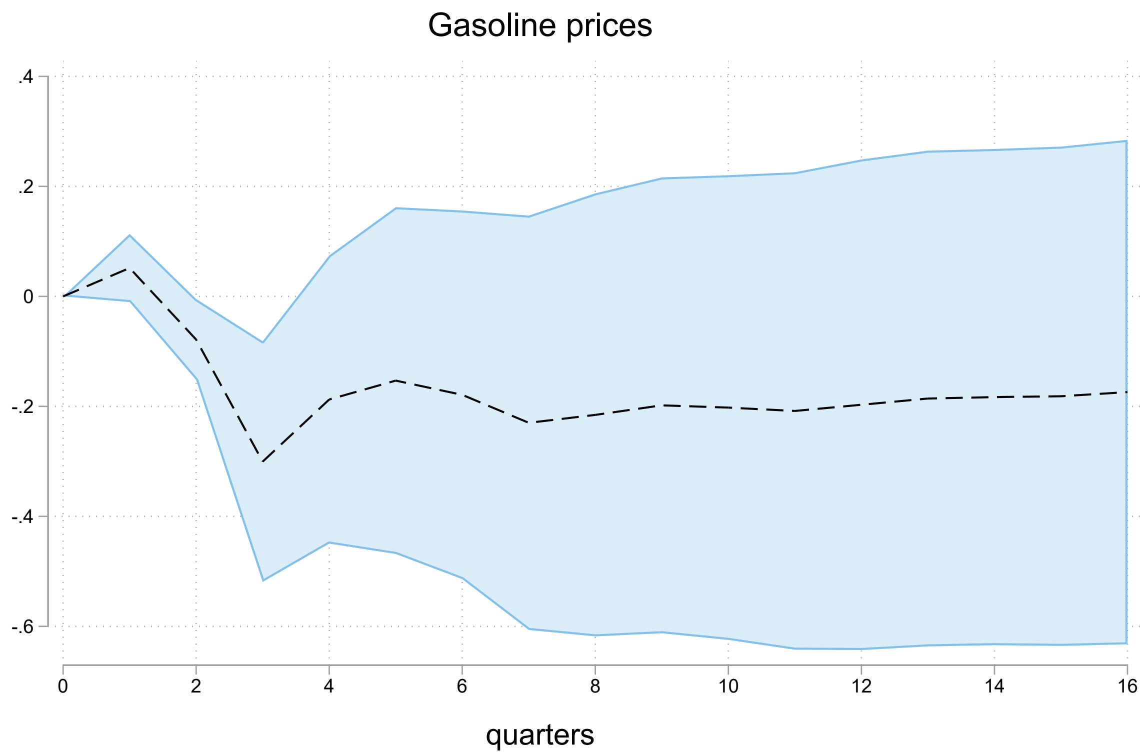
6 Robustness checks

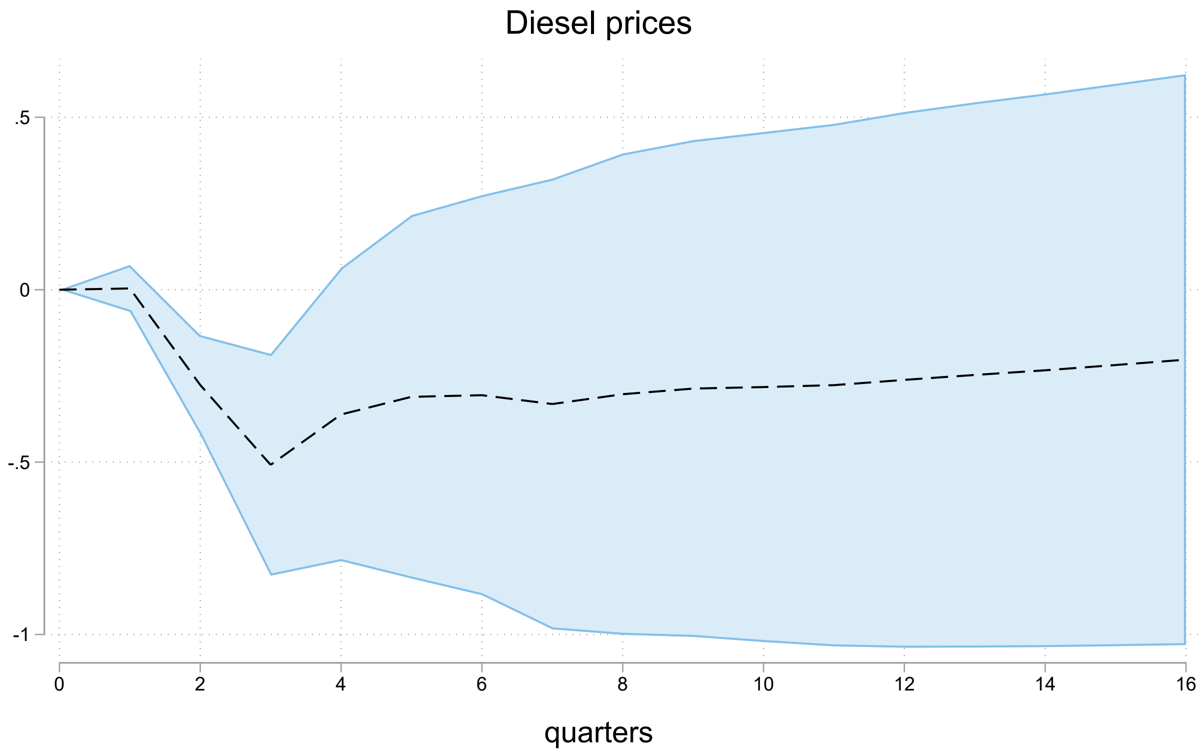
As was already mentioned, I estimate the impact of a shock in natural disasters' intensity using a panel VAR model. As was the case with the local projections approach, I include 4 lags of the variables to control for autocorrelation. Overall, results are similar to what was estimated using the local projections approach, as I find that a 1% shock in natural disasters' intensity has a negative effect in the labour market, as employment falls in the short-term and unemployment raises in the long-term, albeit the latter not statistically significant. Estimates showcase as well that hydrocarbon prices fall in the short-term, especially gasoline and diesel. Interestingly enough, results do not seem to show signs of potential reallocation of disposable income in the debt market, as both consumption and household debt decrease immediately. Overall, my results under the panel VAR model suggest that a 1% shock in natural disasters' intensity has a significant negative long-term effect on GDP, as was the case in the local projections model, albeit much higher at an accumulated 0.170%.

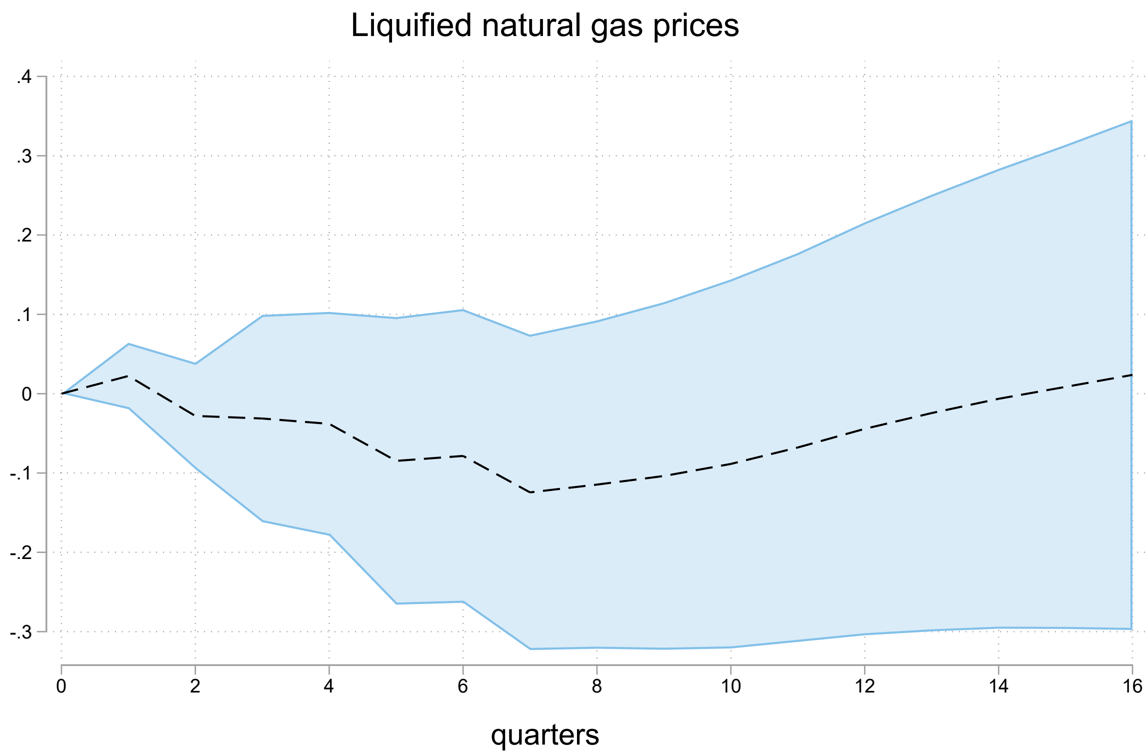
Figure 4: Impulse response functions from a 1% natural disasters' intensity shock

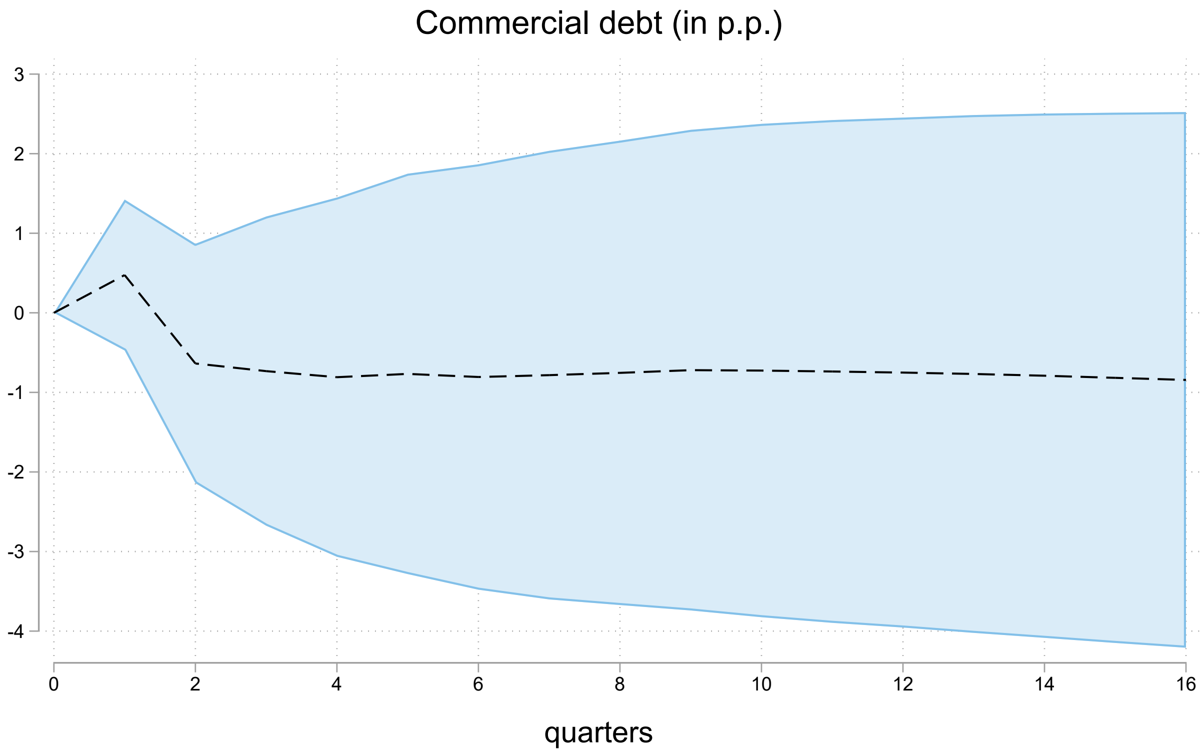



Unemployment rate (in p.p.)
6
4
2
0
-2
-4
0
2
4
6
8
10
12
14
16
quarters

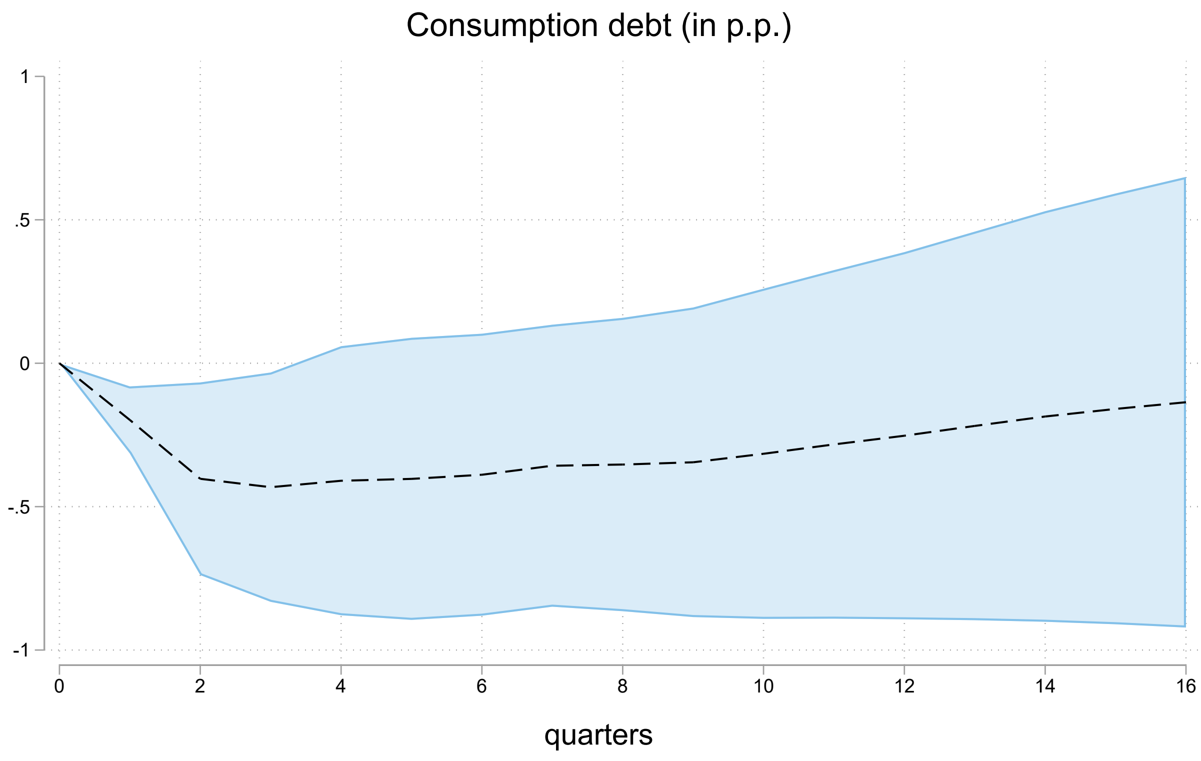

Gasoline prices
.4
.2
0
-.2
-.4
-.6
0
2
4
6
8
10
12
14
16
quarters


Diesel prices
.5
0
-.5
-1
0
2
4
6
8
10
12
14
16
quarters

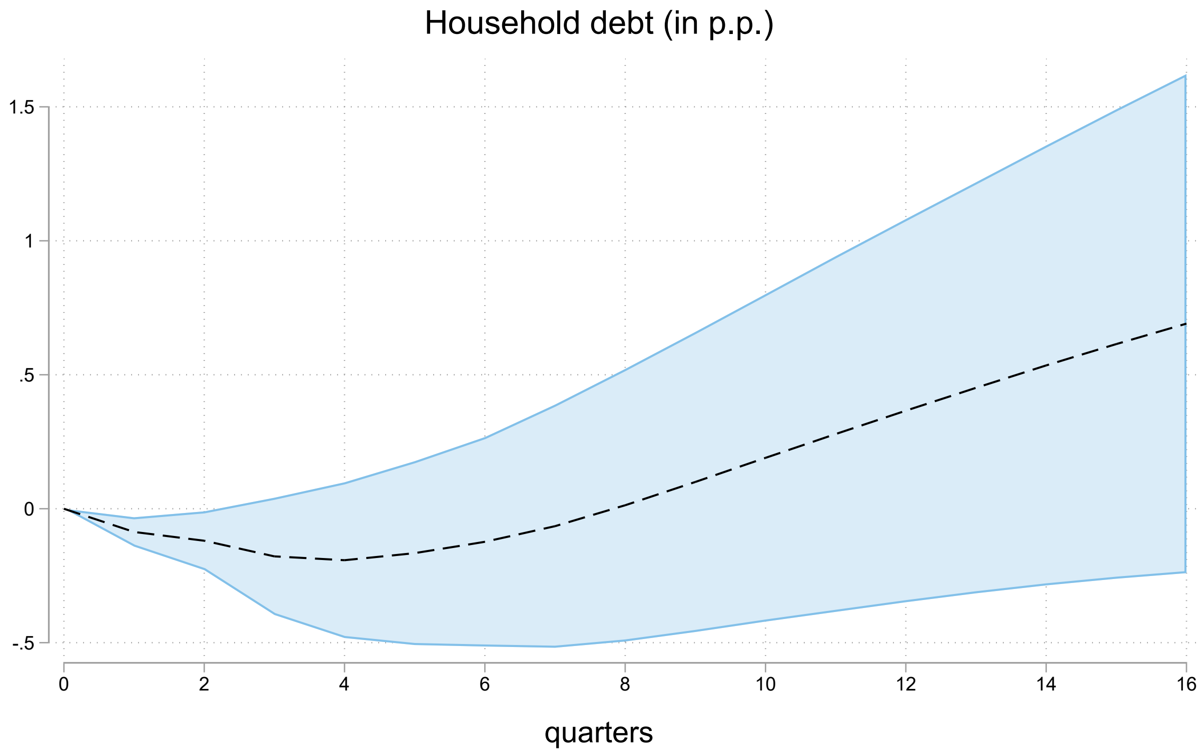

Liquified natural gas prices
.4
.3
.2
.1
0
-.1
-.2
-.3
0
2
4
6
8
10
12
14
16
quarters

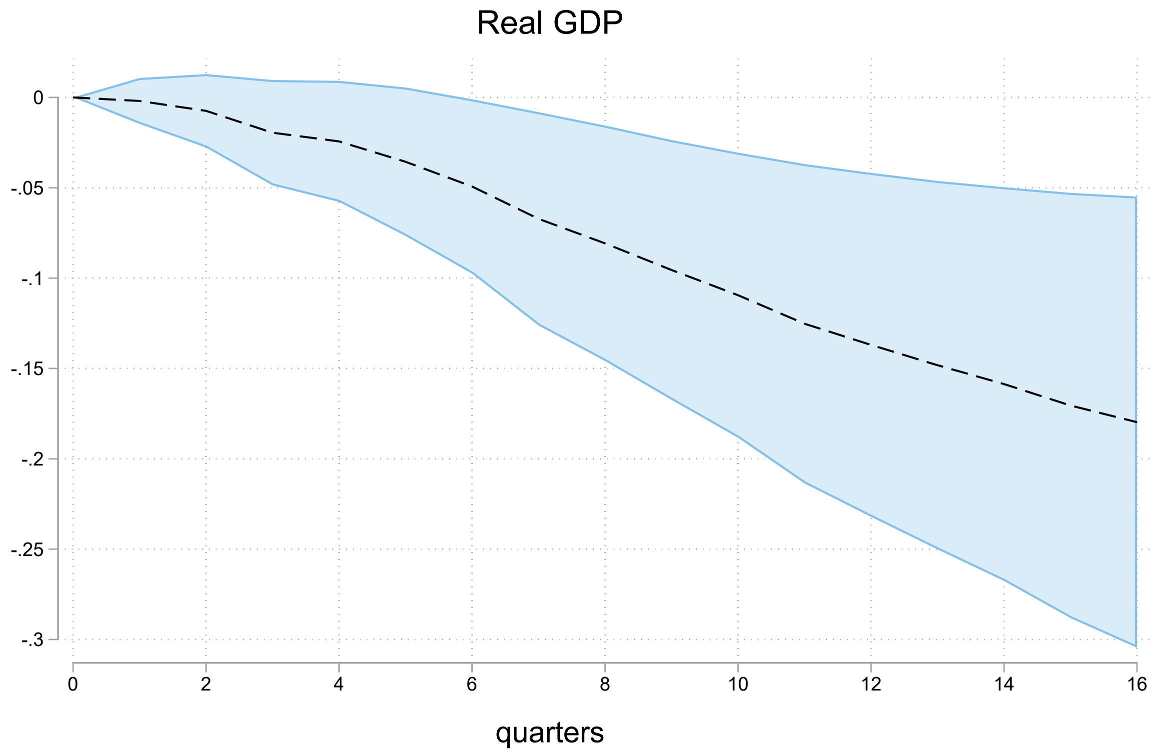


Commercial debt (in p.p.)
3
2
1
0
-1
-2
-3
-4
0
2
4
6
8
10
12
14
16
quarters



Consumption debt (in p.p.)
1
.5
0
-.5
-1
0
2
4
6
8
10
12
14
16
quarters


Household debt (in p.p.)
1.5
1
.5
0
-.5
0
2
4
6
8
10
12
14
16
quarters



Note: shaded areas corresponds to 90% confidence bands.

7 Conclusion and Policy Implications

By relying on a local projections method, this paper addresses how frequency and intensity of natural disasters impact at a local level, focusing on Chilean regions at a quarterly basis for the period 2009-2025. This paper addresses how these factors interplay at a local level, focusing on Chilean regions at a quarterly basis for the period 2009-2025. To analyze intensity, I rely on the local projections method and find that on average, a 1% shock in natural disasters' intensity has an immediate negative effect in employment by 0.057%, and an immediate negative effect on the debt market, increasing the household debt by 0.123 p.p. Overall, my results suggest that a 1% shock in natural disasters' intensity has an immediate positive effect in real GDP by 0.015%, and a significant long-term negative effect on GDP by 0.054%, potentially showing signs of hysteresis. On the other hand, to analyze natural disasters' frequency, I rely on a local projections difference-in-differences (LP-DID) estimator and find that those Chilean regions that suffer a natural disaster, are more likely to experience short-term decreases in employment and GDP by 0.005% and 0.003%, respectively. I rely on a panel VAR model to estimate the impact of natural disasters' intensity as robustness checks, and find that my original conclusions hold: natural disasters have a short-term negative effect on employment at 0.005% and a long-term negative effect on growth at 0.170%.

I believe this work will positively contribute to the literature of natural disasters in emerging markets, as it highlights their effects at a regional level. In a world of increasing environmental challenges, policymakers in emerging markets must incorporate the impact of these shocks in their models, to correctly address the responses in government expenditure via financial aid or assistance to households, to offset the negative effects on income, leverage and growth.

Despite some interesting findings, this work has several limitations that I would like to highlight. Firstly, it is focused on Chile, where natural disasters such as earthquakes are quite common historically, which might limit the external validity of this work. This is, Chile's economy has learnt from past disasters, so the estimates in this paper might be incorporating the response of the Chilean government to offset these shocks. And secondly and as already highlighted, this paper relies on the EM-DAT database to construct the regional database of natural disasters, which has been found to perceive some biases. Nevertheless, I am confident this paper will contribute to the literature of natural disasters and its impact on macroeconomic variables on emerging markets; and to the literature of natural disasters at a local level.

8 Statements and Declarations: competing interests

I disclose there exists no conflict of interest.

9 Funding information

I disclose no funding was involved in this paper.

References

[1] Beirne, J., Park, D., Saadaoui, J. and Uddin, G. S. (2025): “Impact of climate vulnerability on fiscal risk: do religious tensions and financial development matter?”, Working Paper.

[2] Blanchard, O. J. and Jordi, G. (2007): ”The Macroeconomic Effects of Oil Price Shocks: Why are the 2000s so Different from the 1970s?”, MIT Department of Economics Working Paper No. 07-21.

[3] Cavallo, E., Becerra, O. and Acevedo, L. (2021), ”The impact of natural disasters on economic growth”, IADB Working Papers.

[4] Cevik, S. and Jalles, J. (2024): ”Eye of the storm: the impact of climate shocks on inflation and growth”, Review of economics, vol. 75, pp. 109-138.

[5] Chakrabarti, S., Naoaj, M. S., Yang, Y., Zhang, S. and Chen, X. (2023), “The impact of natural disasters on economic growth: a comparative analysis between developed and developing countries”, Working Paper.

[6] Costa, H. and Hooley, J. (2025), “The macroeconomic implications of extreme weather events”, OECD Economics Department.

[7] Dube, A., Girardi, D., Jordà, Ò. and Taylor, A. M. (2025), “A local projections approach to difference-in-differences”, Journal of Applied Econometrics.

[8] Duprey, T., and Fernandes, V. (2025), “Natural disasters and inflation in Canada”, Staff Analytical Note.

[9] Felbermayr, G. and Gröschl, J. (2013), “Naturally negative: the growth effects of natural disasters”, CESIFO Working Paper No. 4439.

[10] Fomby, T., Ikeda, Y. and Loayza, N. (2011), ”The growth aftermath of natural disasters”, Journal of Applied Econometrics, Vol. 28, pp. 412-434.

[11] Fuje, H., Yao, J. and Choi, S. M. (2023), “Fiscal impacts of climate disasters in emerging markets and developing economies”, IMF Working Paper.

[12] Ehlers, T., Frost, J., Madeira, C. and Shim, I. (2025), “Macroeconomic impact of extreme weather events”, BIS Working Papers.

[13] Hsiang S. M. and Jina, A. S. (2014), "The causal effect of environmental catastrophe on long-run economic growth: evidence from 6,700 cyclones", NBER Working Papers.

[14] Jordà, Ò. (2005): "Estimation and inference of impulse responses by local projections", American Economic Review, 95(1), pp. 161–182.

[15] Känzig, D. R. (2021), "The Macroeconomic Effects of Oil Supply News: Evidence from OPEC Announcements", The American Economic Review, Vol. 111, No. 4, pp. 1092-1125.

[16] Keen, B. D. and Pakko, M. R. (2011), "Monetary policy and natural disasters in a DSGE model", Southern Economic Association, Vol. 77, pp. 973–990.

[17] Lloyd, S. and Manuel, E. (2024), "Controls, not shocks: estimating dynamic causal effects in macroeconomics", Bank of England Staff Working Paper No. 1079.

[18] Lusompa, A. (2020): "Local Projections, Autocorrelation, and Efficiency", Federal Reserve Bank of Kansas City Research Papers.

[19] Mishra, P., Montiel, P. J. and Spilimbergo, A. (2012), "Natural disasters, climate change, and sovereign risk", International Finance Discussion Papers 1291, Washington: board of governors of the Federal Reserve System.

[20] Montiel Olea, J. L. and Plagborg-Møller, M. (2021): "Local projection inference is simpler and more robust than you think", Econometrica, Vol. 89, pp. 1789-1823.

[21] Plagborg-Møller, M. and Wolf, C. K. (2021): "Local Projections and VARs Estimate the Same Impulse Responses", Econometrica, Vol. 89 (2); pp. 955-80.

[22] Rasmussen, T. N. (2004), "Macroeconomic implications of natural disasters in the Caribbean", IMF Working Papers.

[23] Teber, K., Weynants, M., Gans, F. and Mahecha, M. D. (2025), "“Geo-Disasters: geocoding climate-related events in the international disaster database EM-DAT", Working Paper.

[24] Weicheng, L., Moran, J. R. and Vishvesh, R. (2022), "Natural disasters and scarring effects", IMF Working Papers.

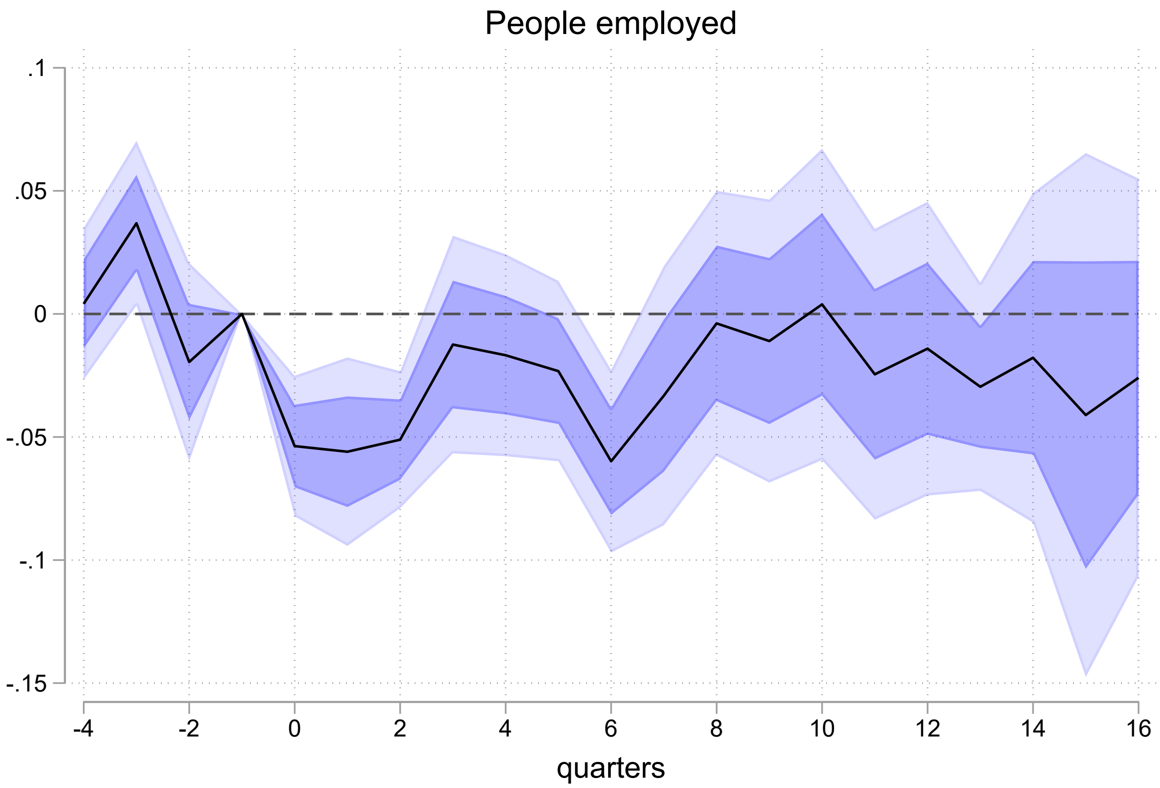
[25] Ugarte-Ruiz, A. (2023), "locproj: A new Stata command to estimate local projections", 2023 Stata Conference from Stata Users Group.

10 Appendix

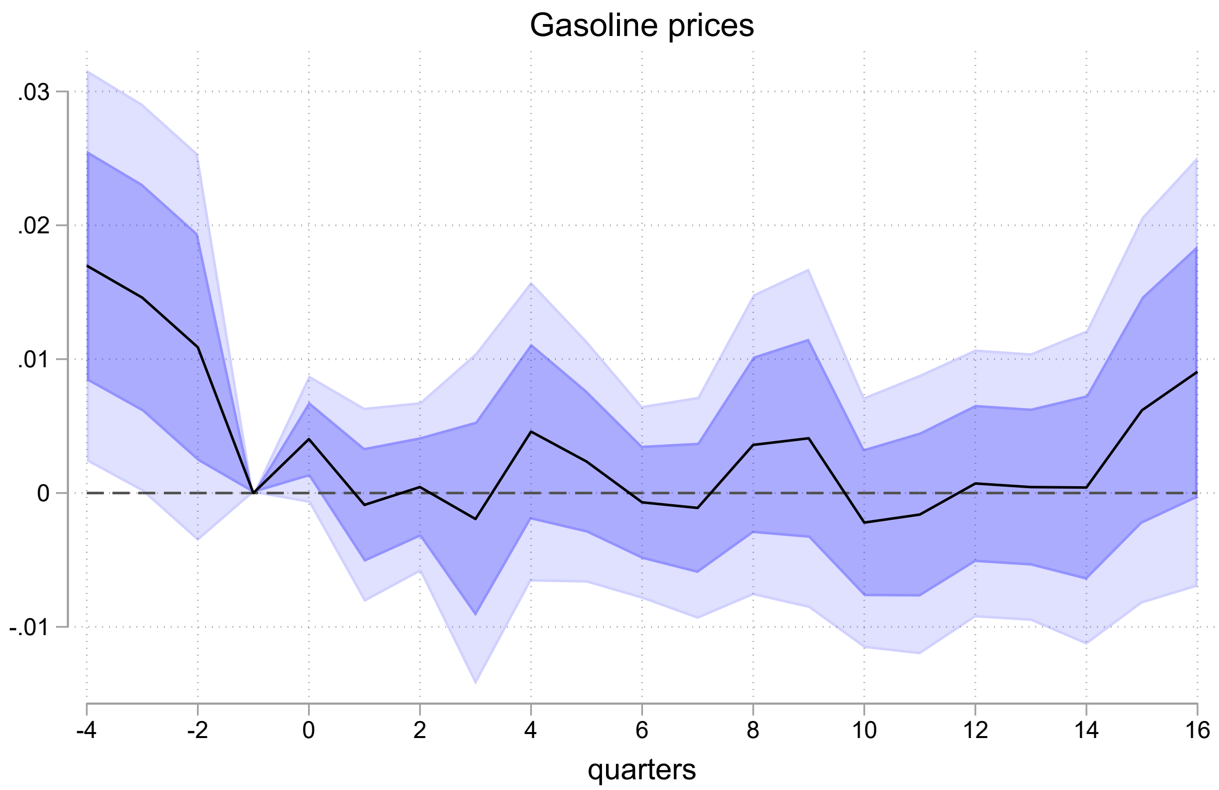
10.1 Sensitivity analysis: 2 and 6 lags as controls

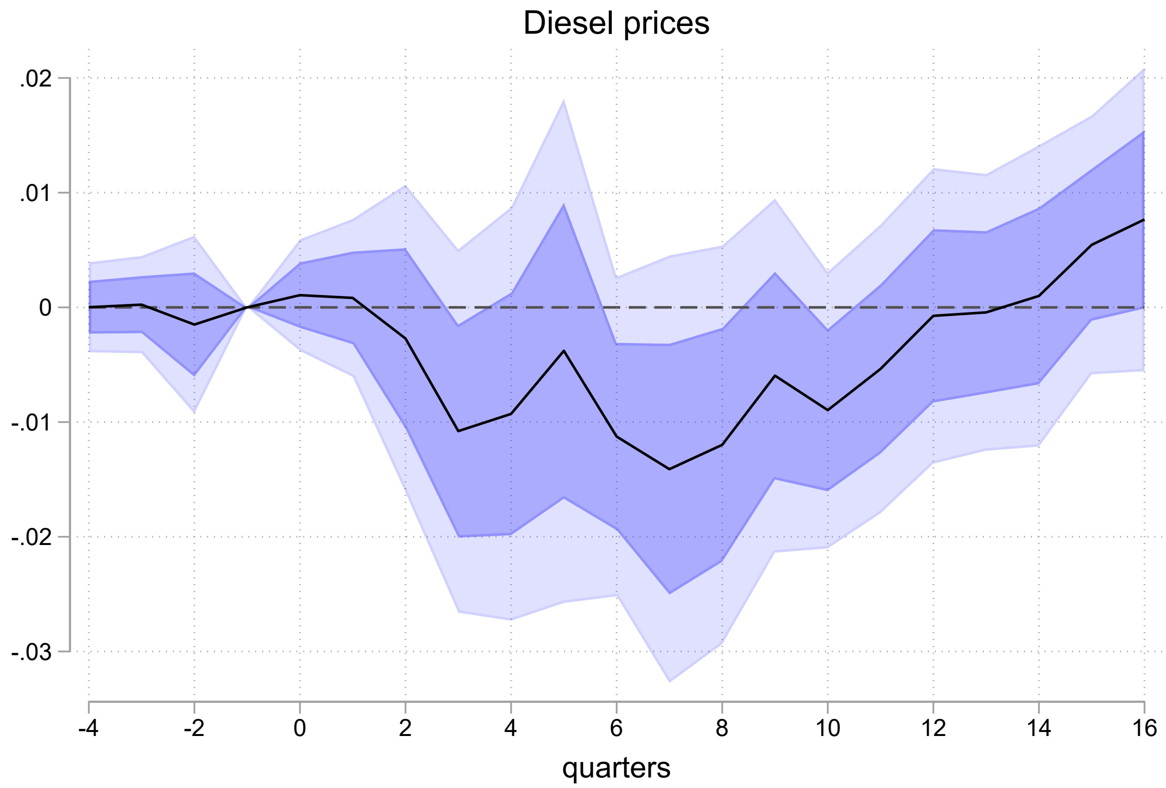
In this subsection, I show estimates using 2 (see Fig. 5) and 6 lags (see Fig. 6) as controls, as opposed to 4 lags as the base model. Results suggest that my prior conclusions hold, although with 2 lags, some effects become not statistically significant.

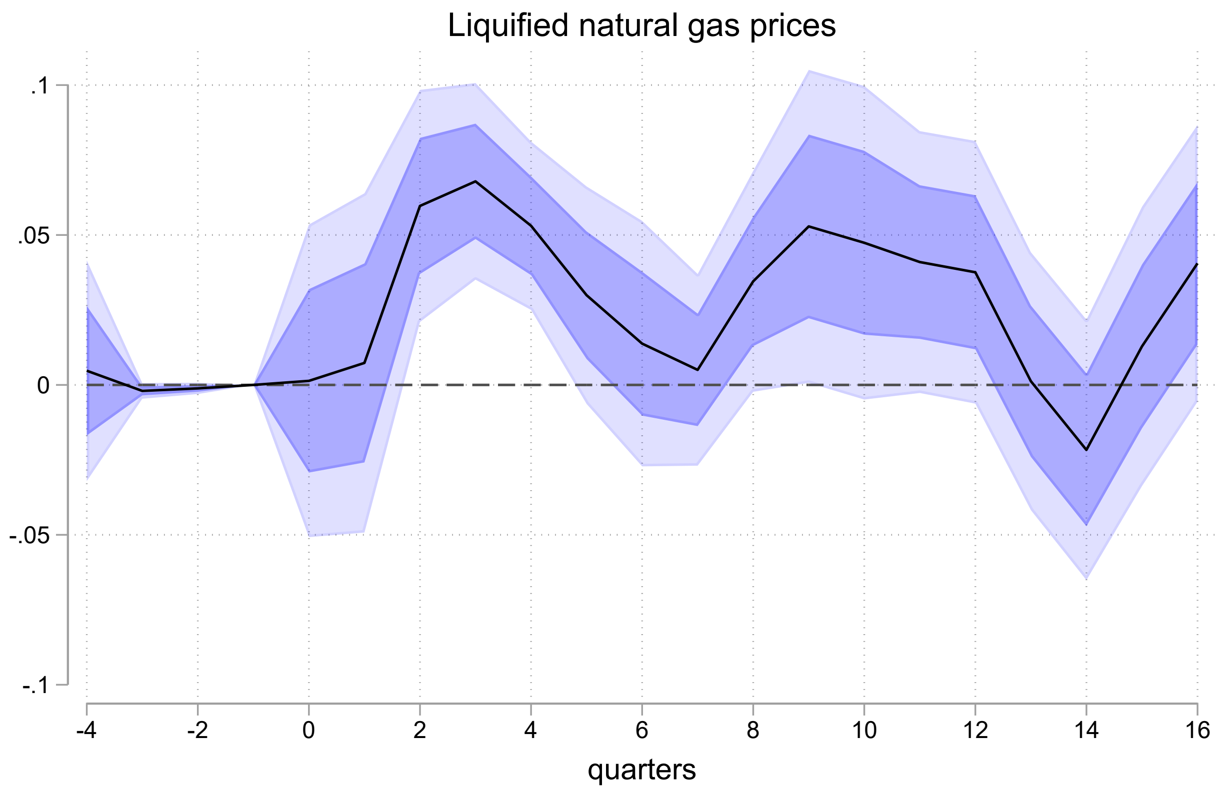
Figure 5: Impulse response functions from a 1% natural disasters' intensity shock using 2 lags as controls

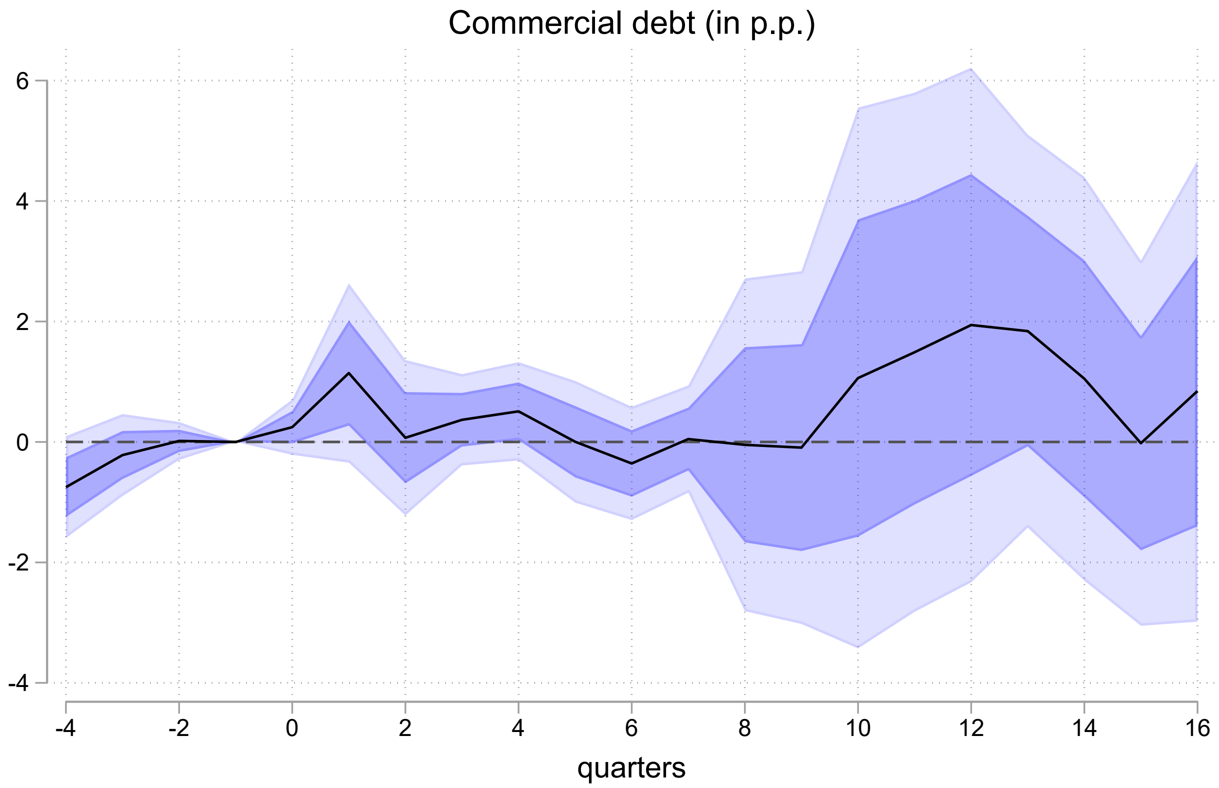


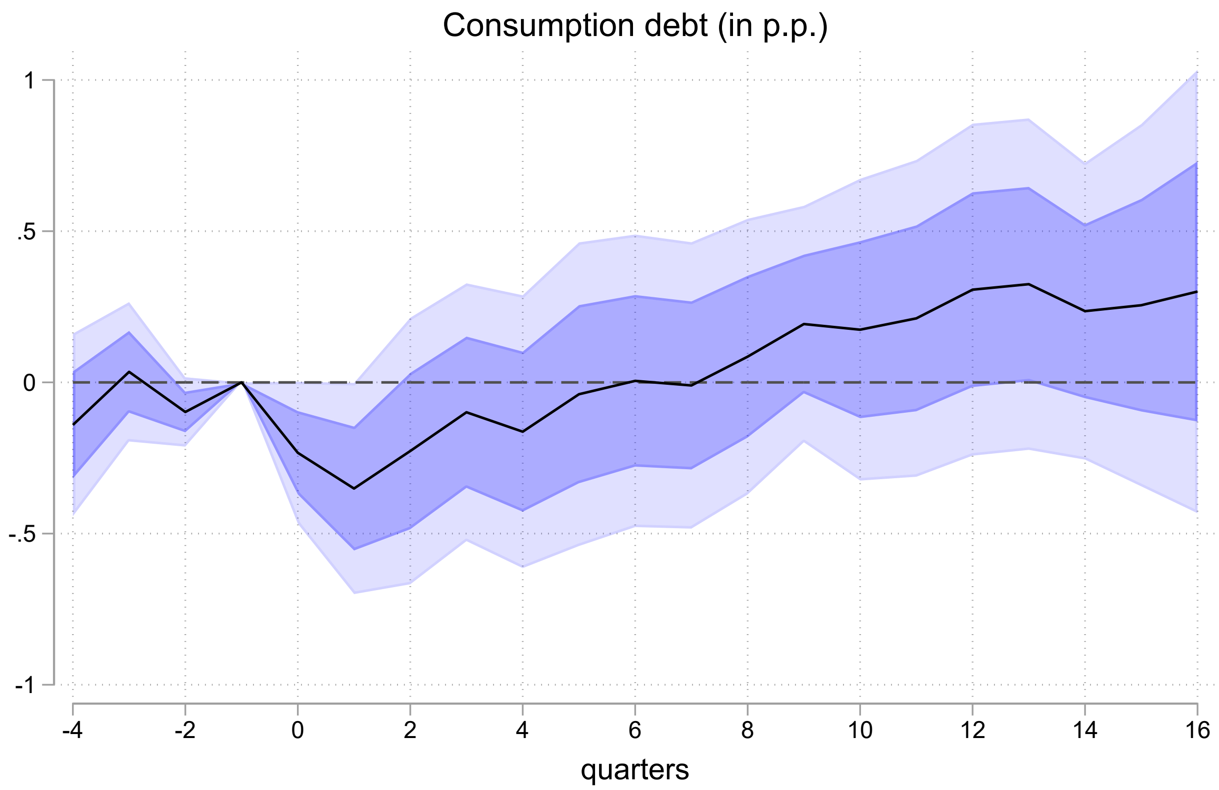

Unemployment rate (in p.p.)
4
3
2
1
0
-1
-2
-3
-4
-2
0
2
4
6
8
10
12
14
16
quarters

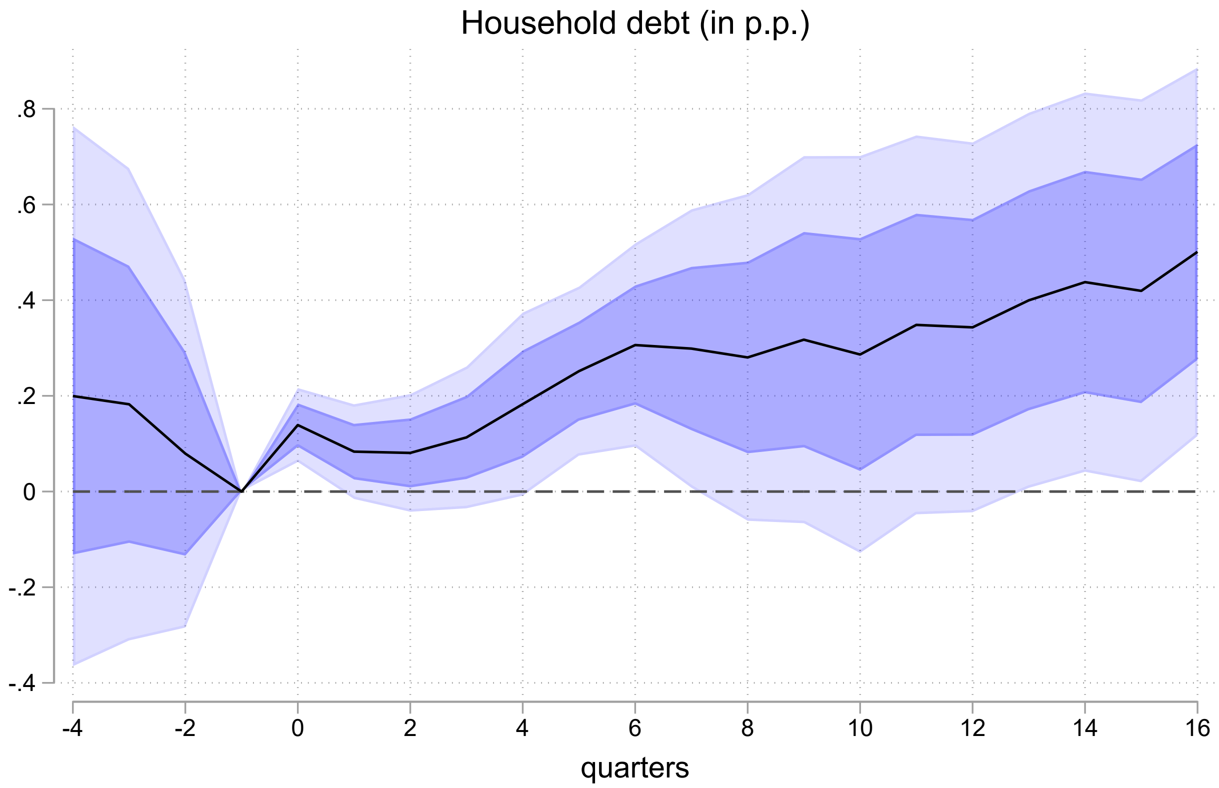

Gasoline prices
.03
.02
.01
0
-.01
-4
-2
0
2
4
6
8
10
12
14
16
quarters

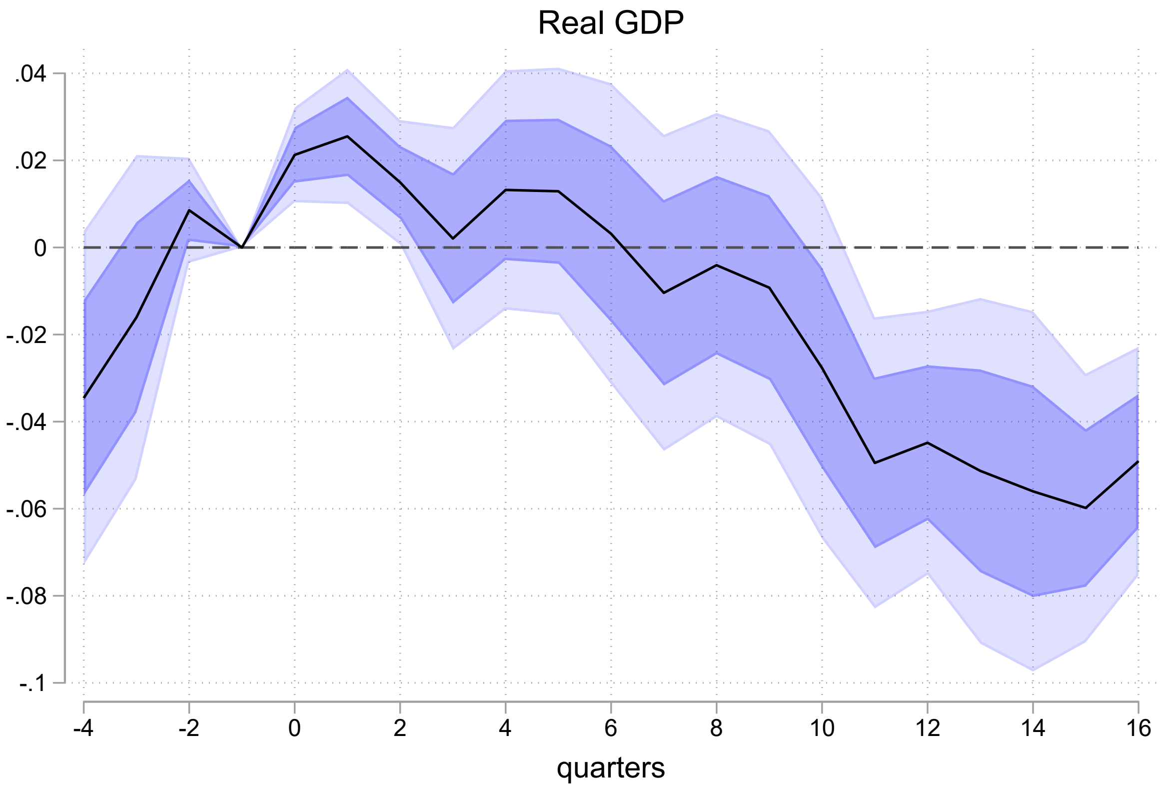

Diesel prices
.02
.01
0
-.01
-.02
-.03
-4
-2
0
2
4
6
8
10
12
14
16
quarters


Liquified natural gas prices
.1
.05
0
-.05
-.1
-4
-2
0
2
4
6
8
10
12
14
16
quarters


Commercial debt (in p.p.)
6
4
2
0
-2
-4
-4
-2
0
2
4
6
8
10
12
14
16
quarters

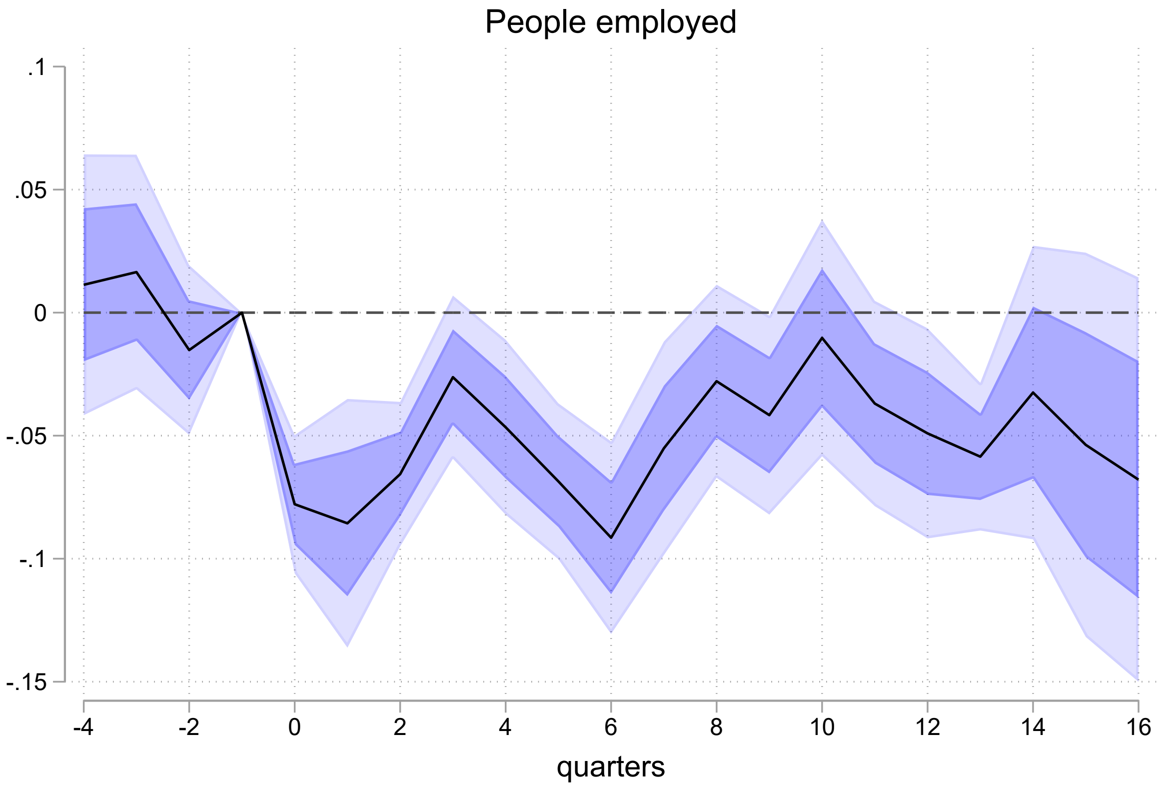

Consumption debt (in p.p.)
1
.5
0
-.5
-1
-4
-2
0
2
4
6
8
10
12
14
16
quarters

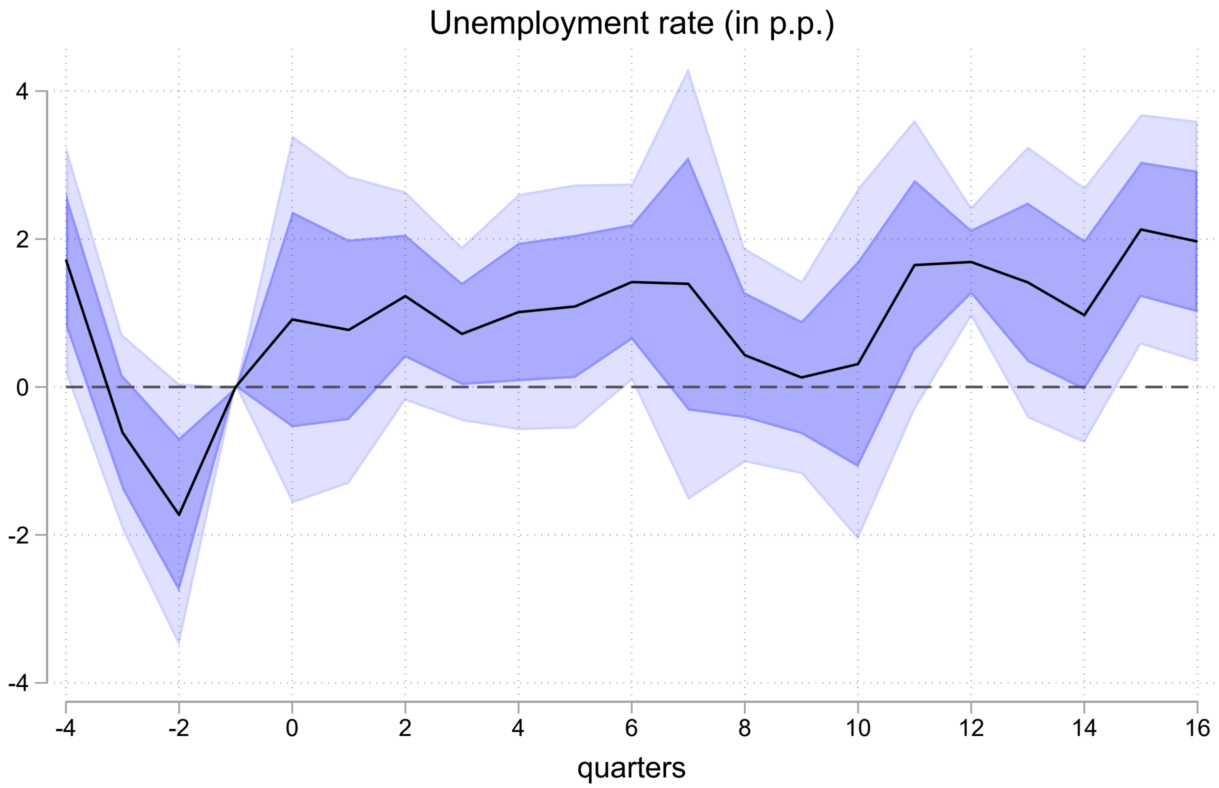

Household debt (in p.p.)
.8
.6
.4
.2
0
-.2
-.4
-4
-2
0
2
4
6
8
10
12
14
16
quarters

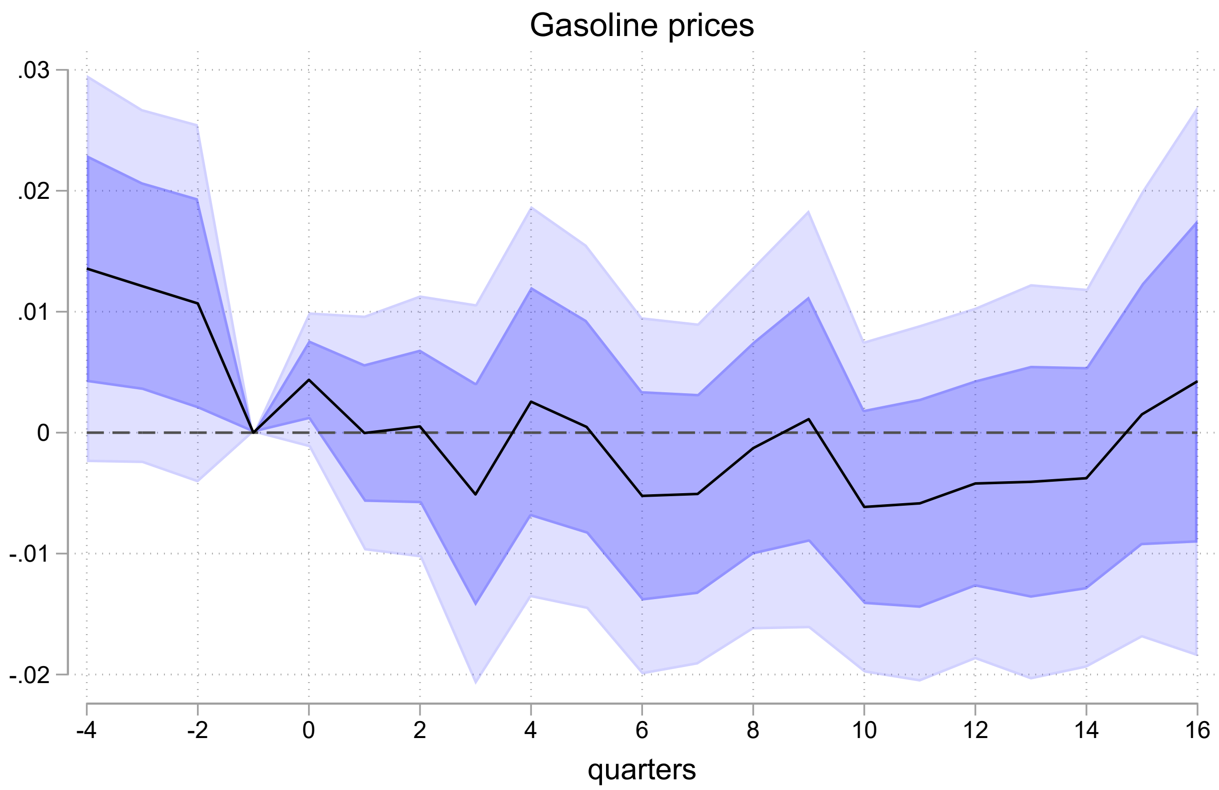


Note: shaded areas corresponds to 90 and 68% confidence bands.

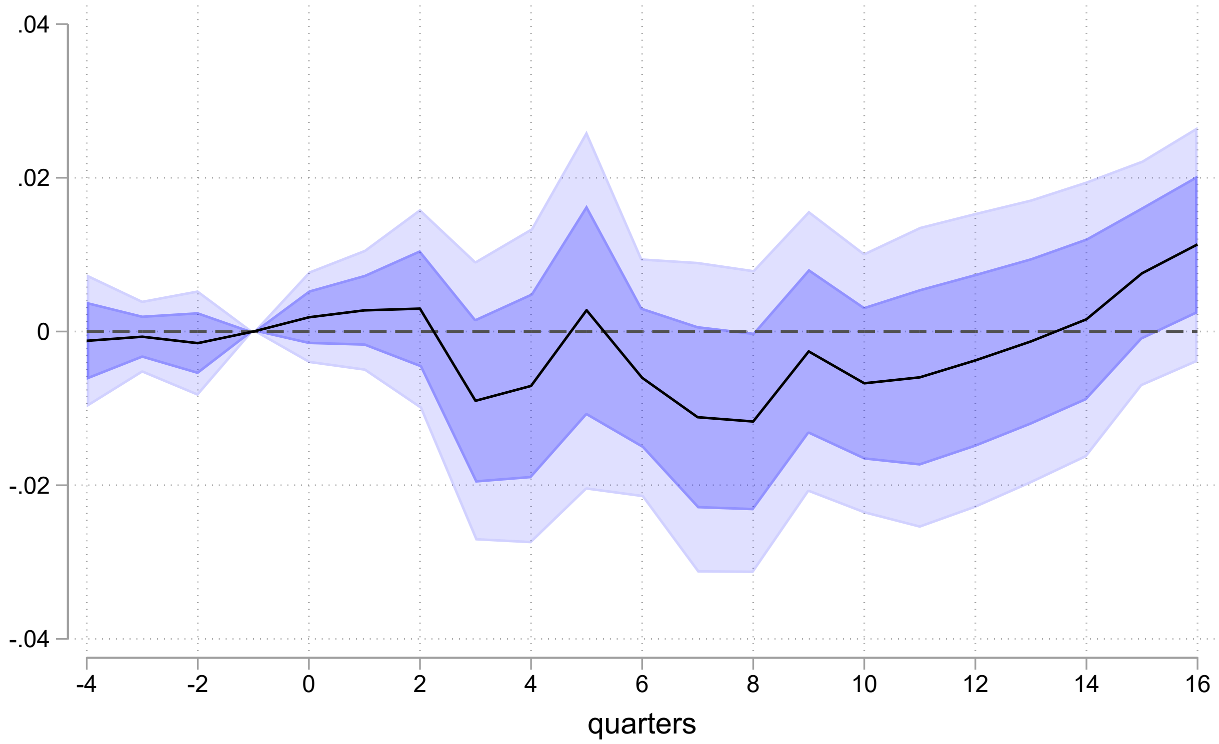
Figure 6: Impulse response functions from a 1% natural disasters' intensity shock using 6 lags as controls



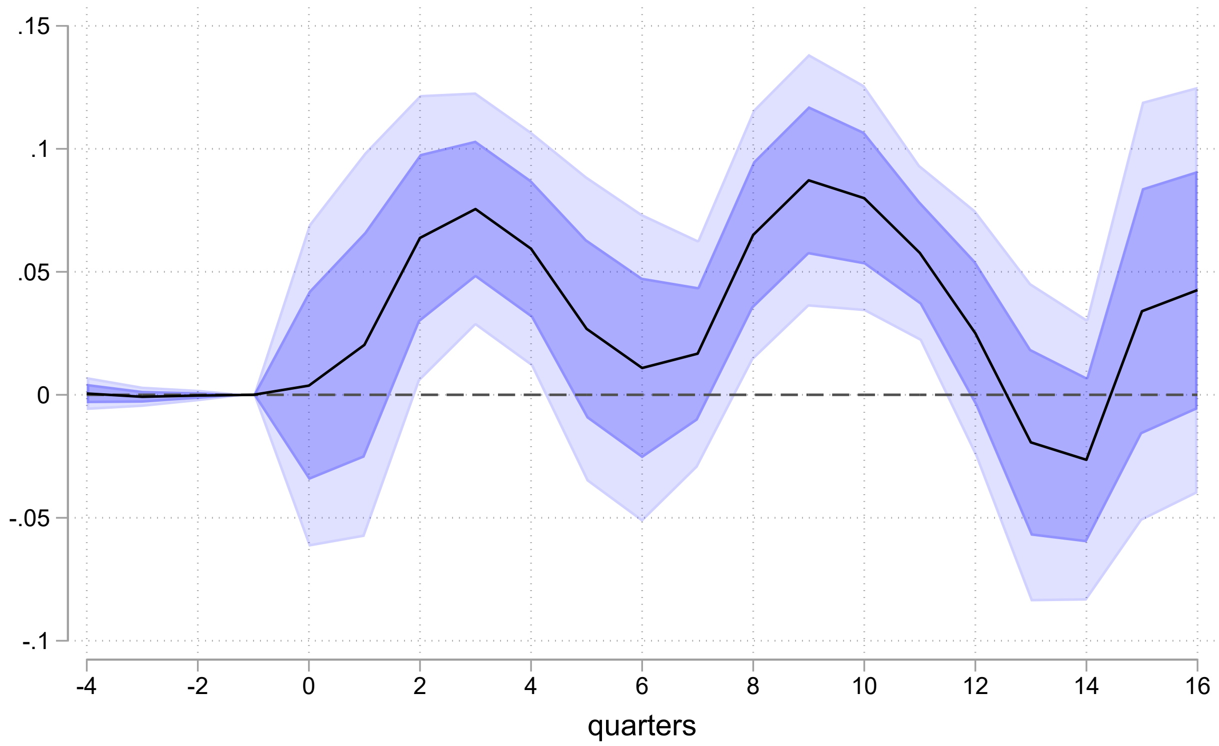

Unemployment rate (in p.p.)
4
2
0
-2
-4
-4
-2
0
2
4
6
8
10
12
14
16
quarters

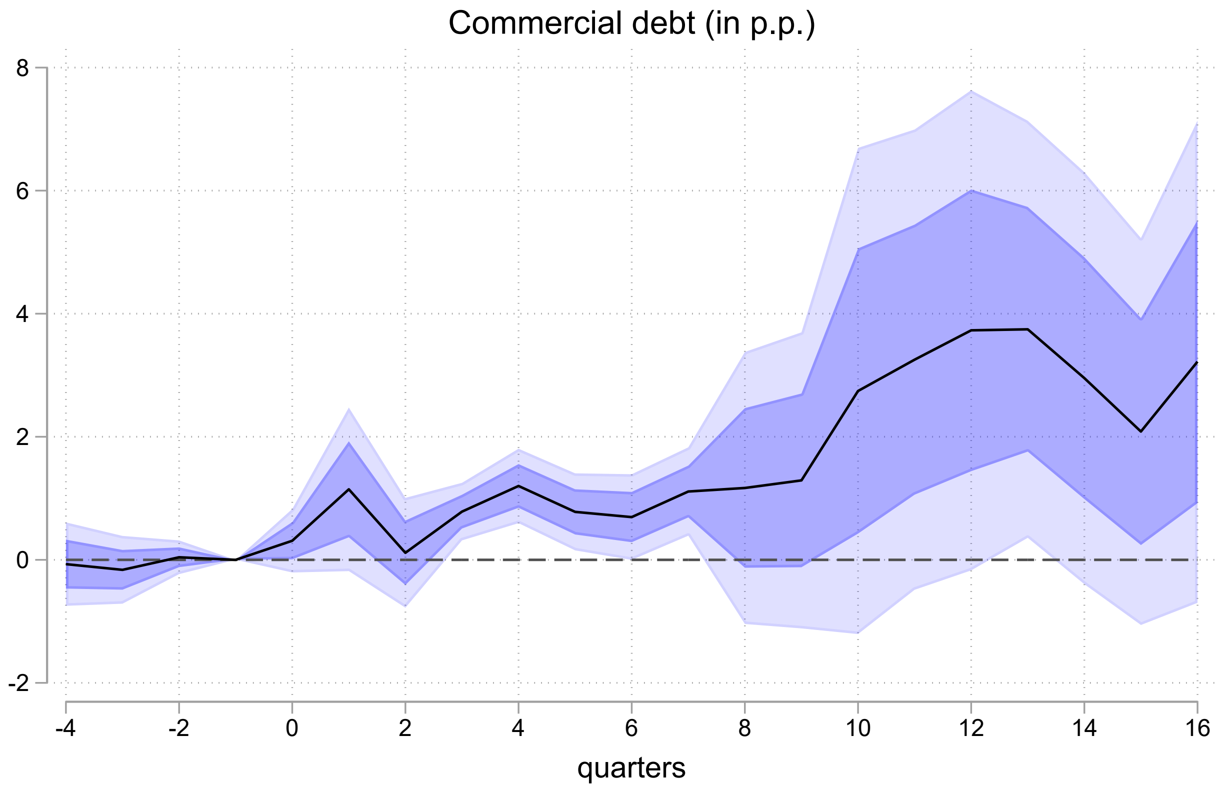

Gasoline prices
.03
.02
.01
0
-.01
-.02
-4
-2
0
2
4
6
8
10
12
14
16
quarters

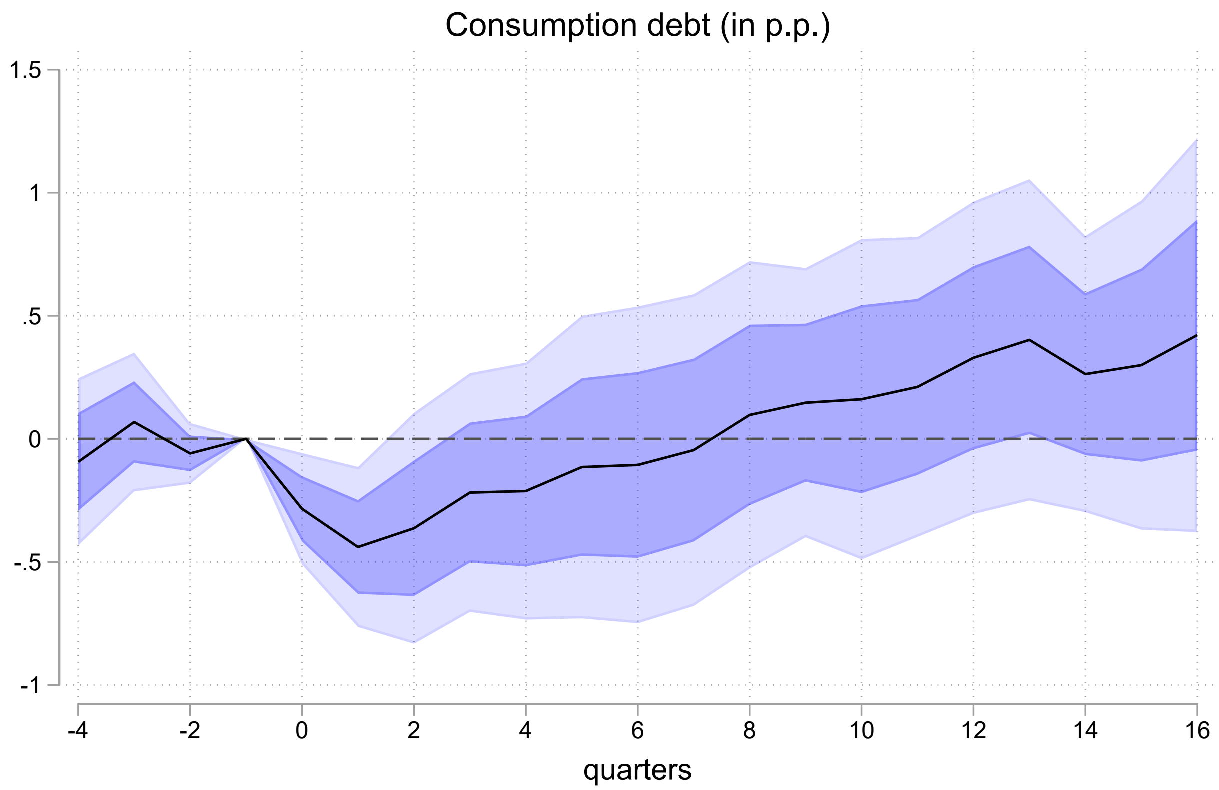
Diesel prices

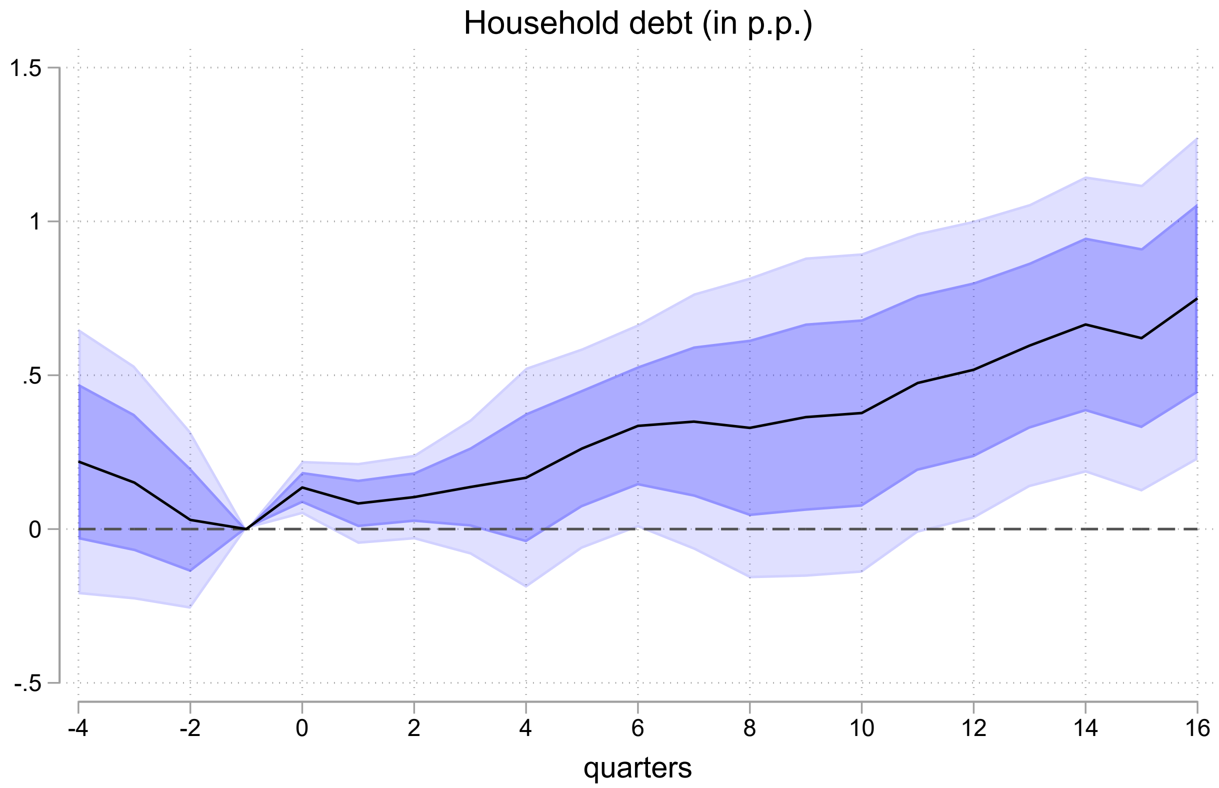


Liquified natural gas prices

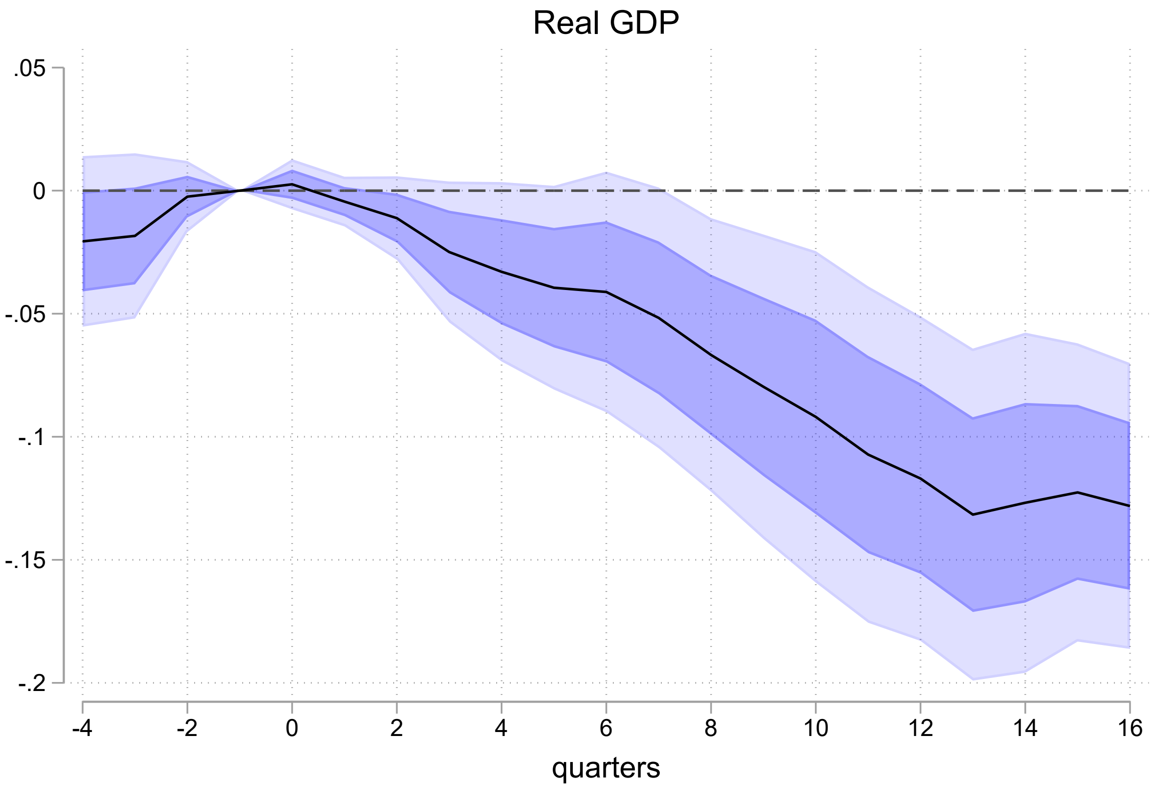



Commercial debt (in p.p.)
8
6
4
2
0
-2
-4
-2
0
2
4
6
8
10
12
14
16
quarters


Consumption debt (in p.p.)
1.5
1
.5
0
-.5
-1
-4
-2
0
2
4
6
8
10
12
14
16
quarters



Household debt (in p.p.)
1.5
1
.5
0
-.5
-4
-2
0
2
4
6
8
10
12
14
16
quarters

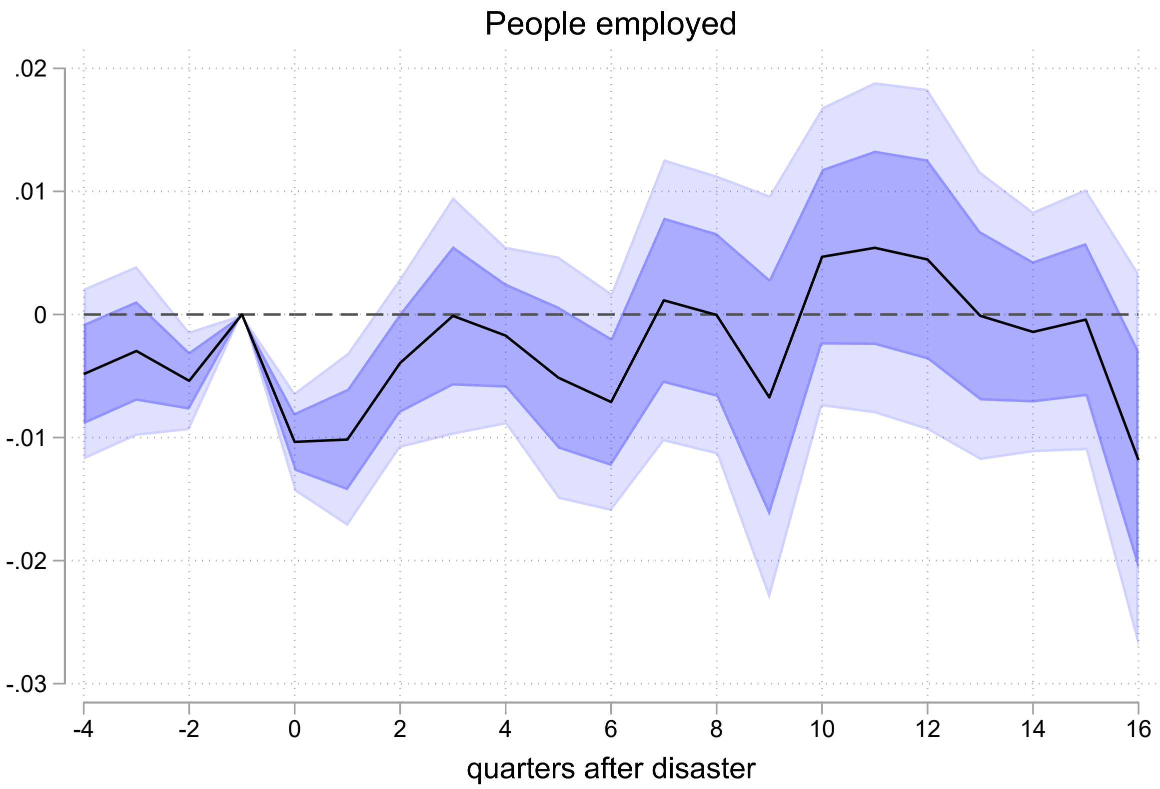


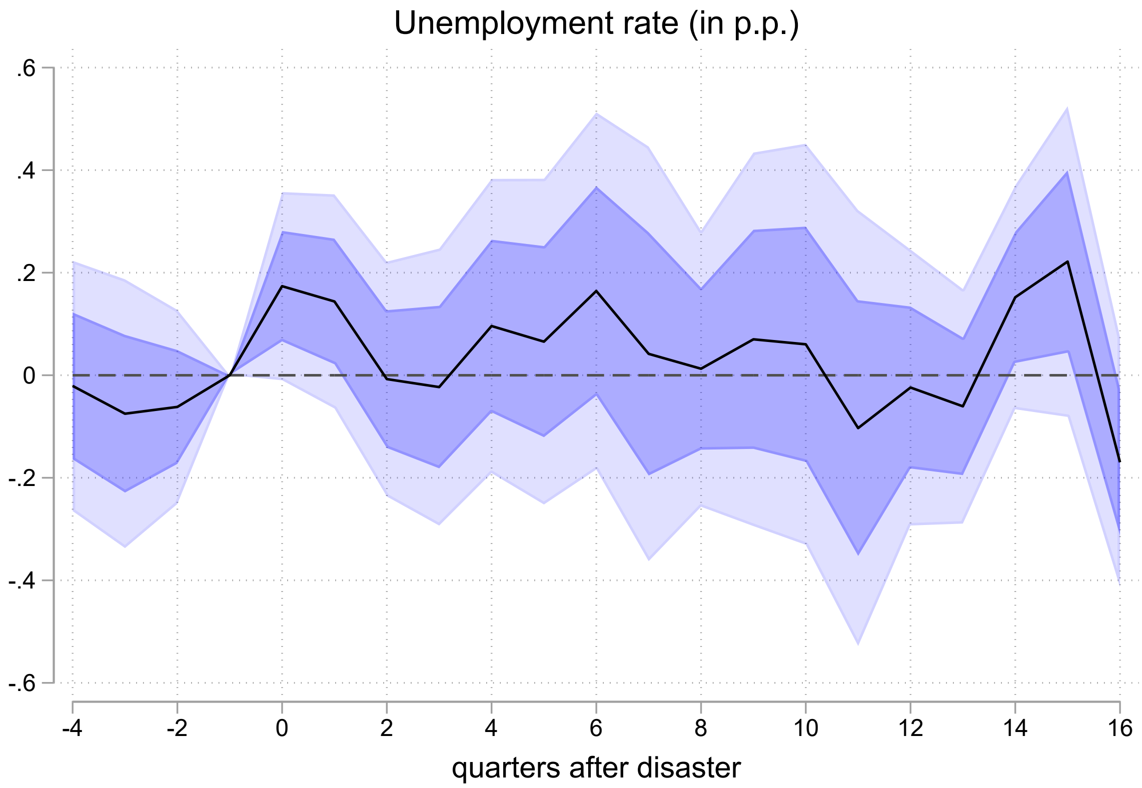
Note: shaded areas corresponds to 90 and 68% confidence bands.

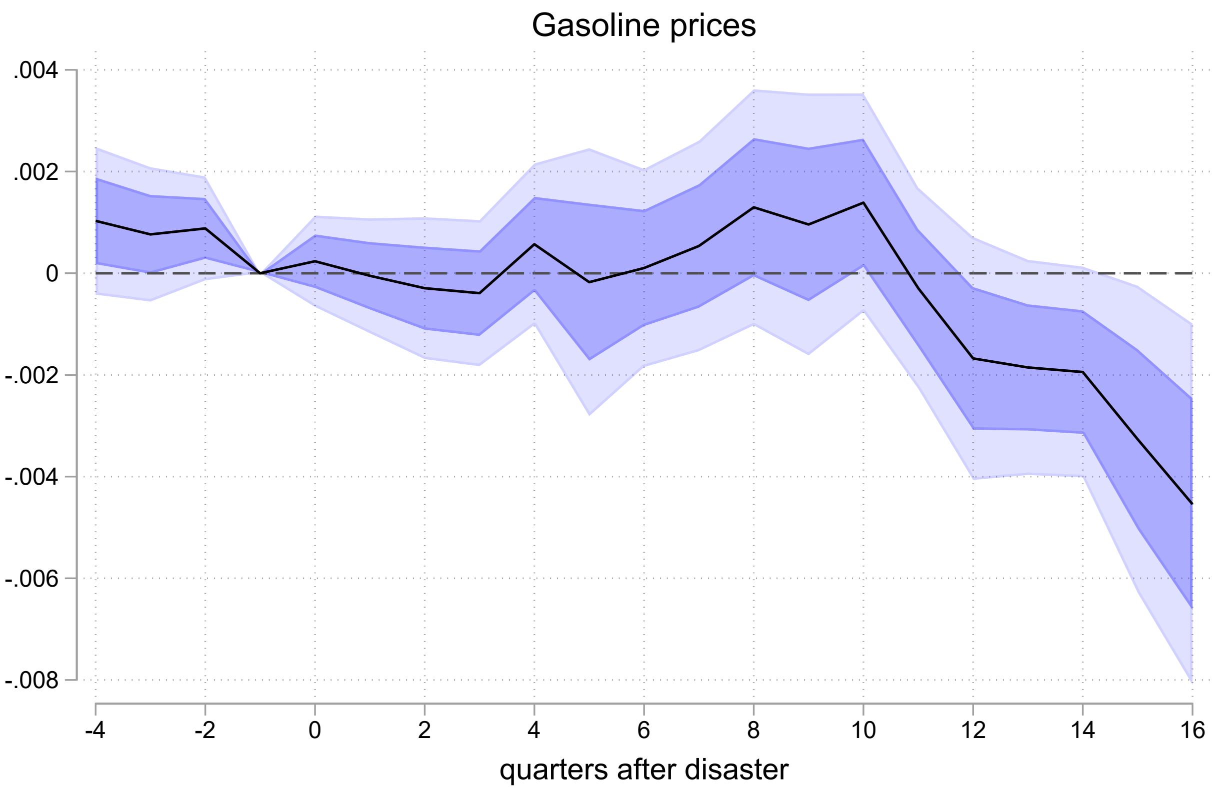
10.2 Sensitivity analysis: average treatment effect using local projections

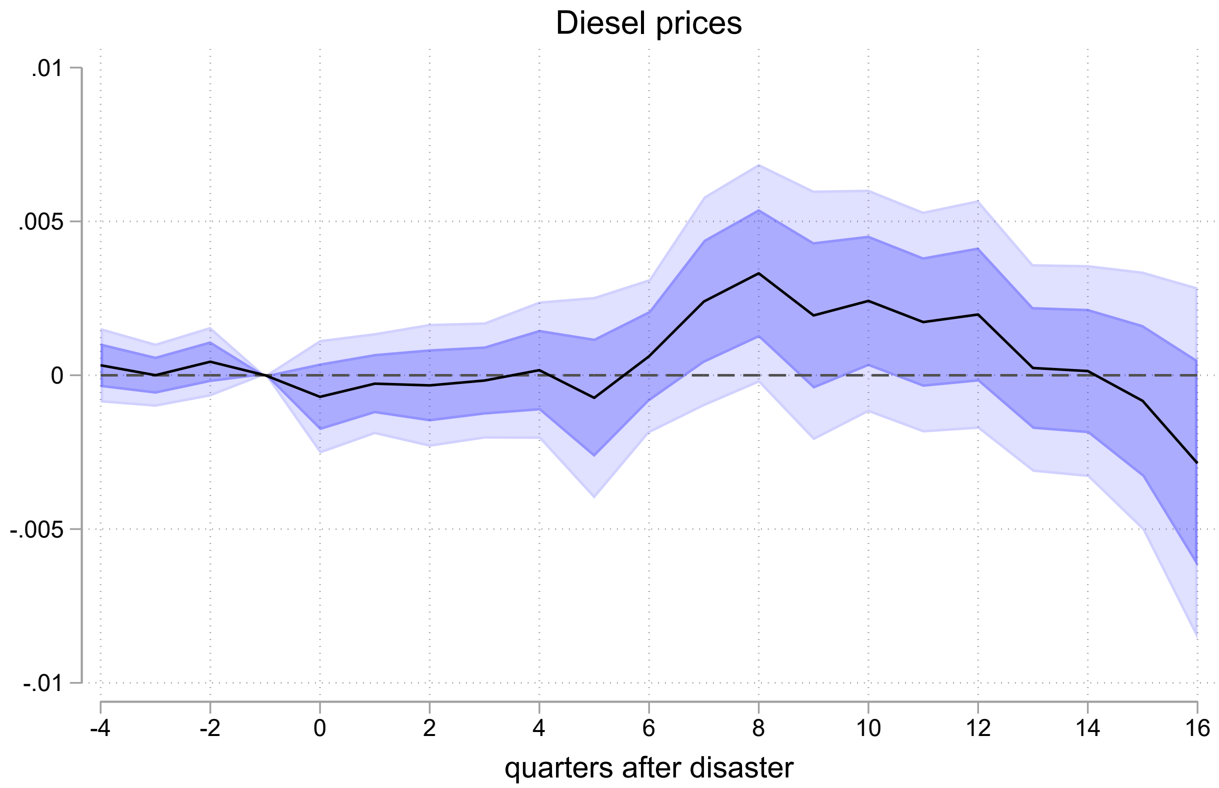
In this subsection, I show the average treatment effect of the occurence of natural disasters using the local projections approach instead of a difference-in-differences estimator. Results suggest that my prior conclusions hold: on average, Chilean regions that suffer a natural disaster are more likely to experience lower immediate employment and GDP by 0.01% 0.05%, respectively (see Fig. 7).

Figure 7: Impulse response functions from a 1% natural disasters' intensity shock

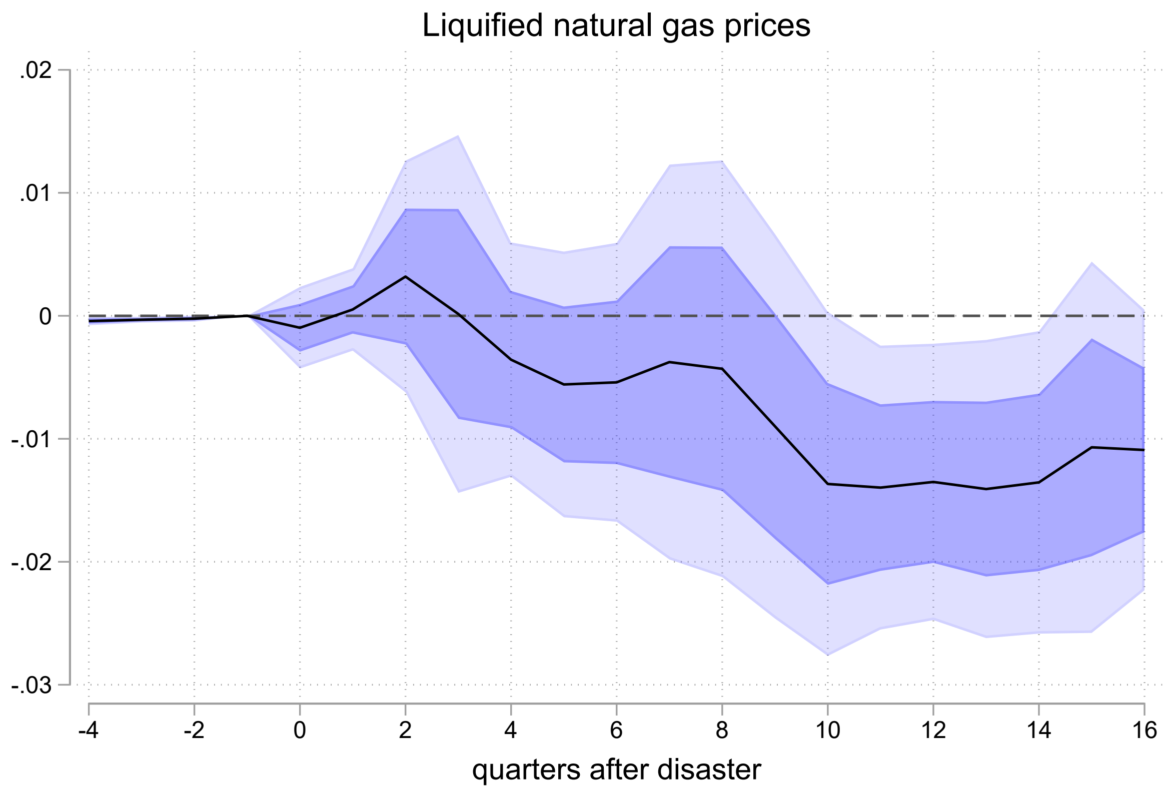



Unemployment rate (in p.p.)
.6
.4
.2
0
-.2
-.4
-.6
-4
-2
0
2
4
6
8
10
12
14
16
quarters after disaster

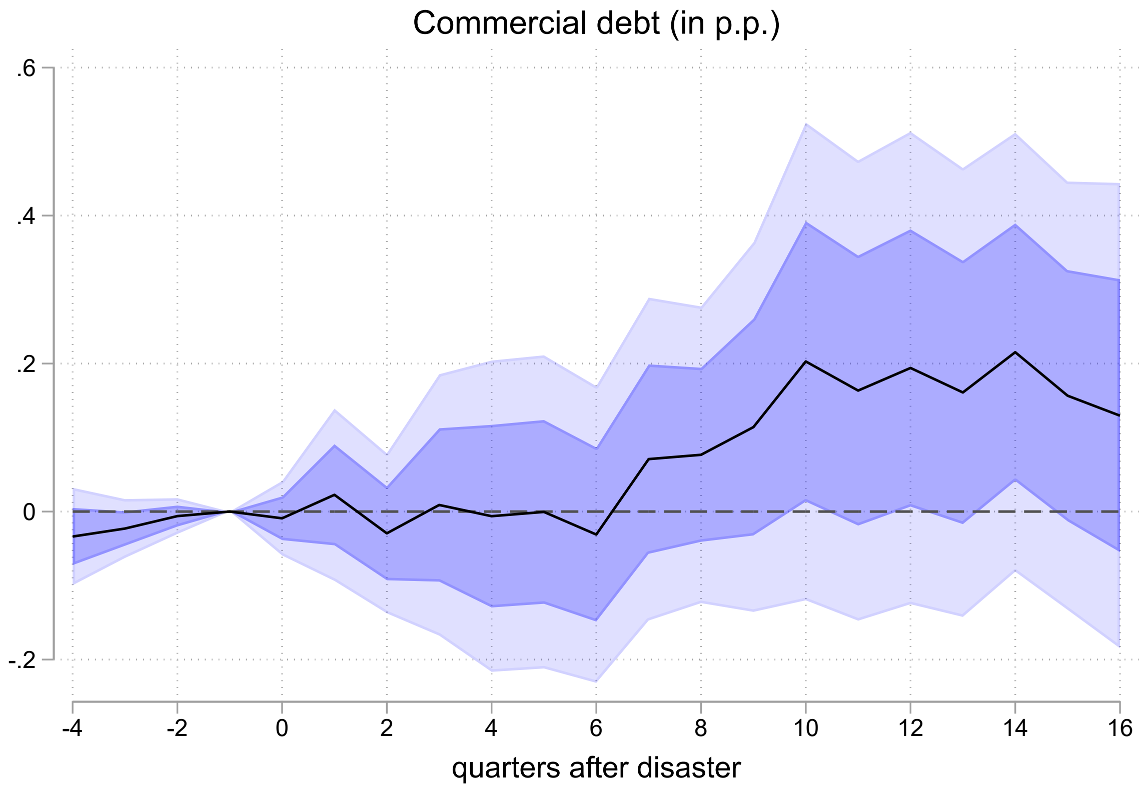

Gasoline prices
.004
.002
0
-.002
-.004
-.006
-.008
-4
-2
0
2
4
6
8
10
12
14
16
quarters after disaster

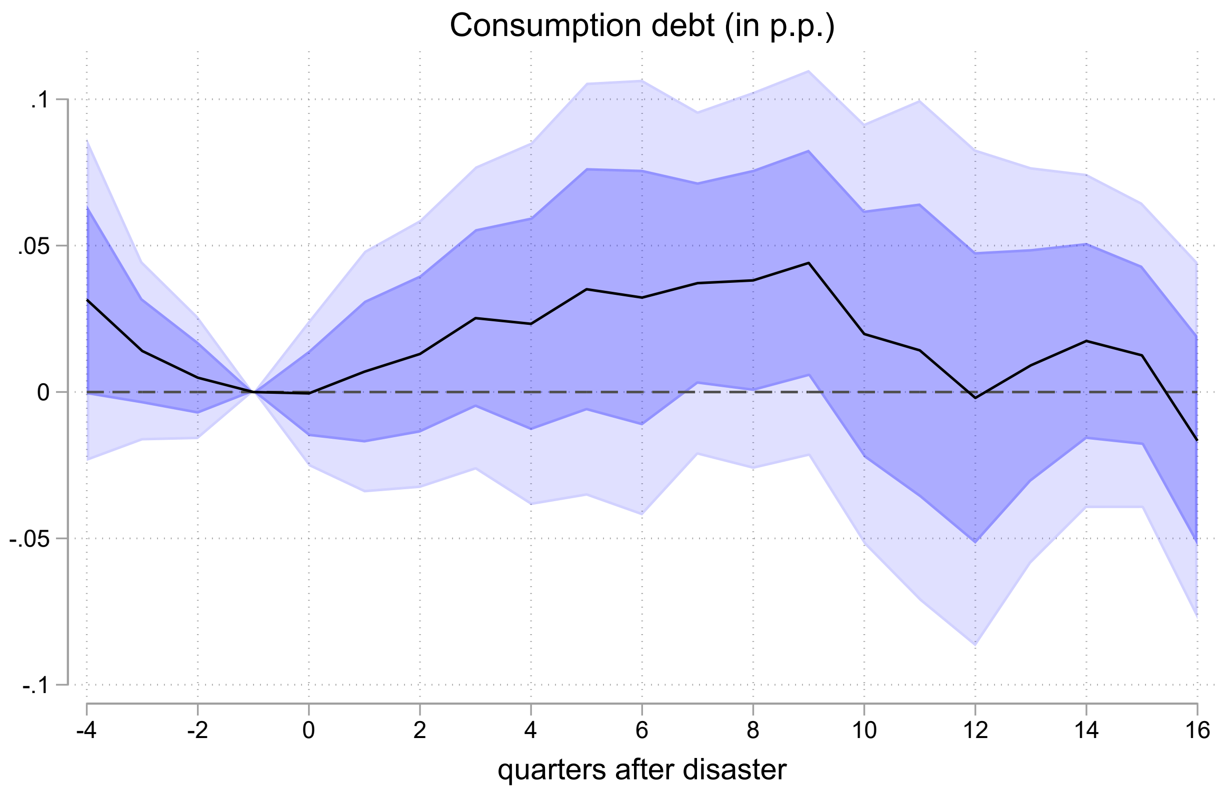


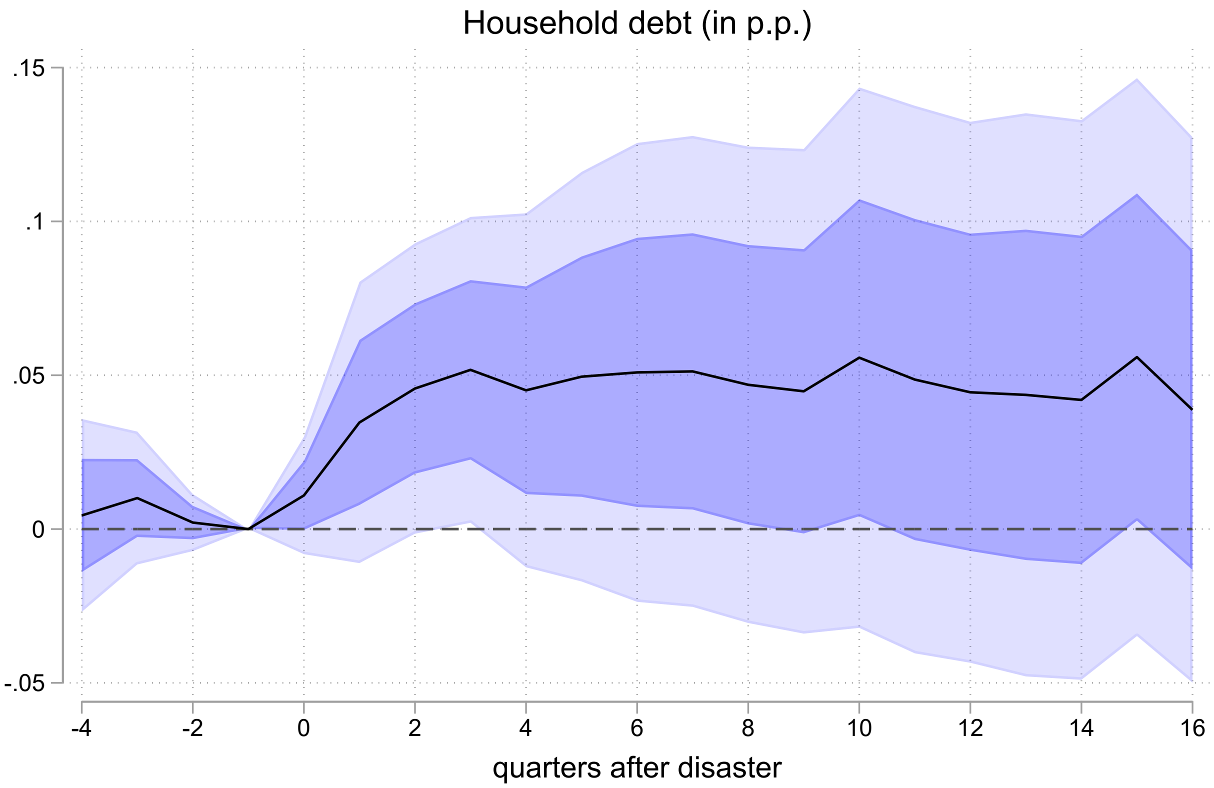
Diesel prices
.01
.005
0
-.005
-.01
-4
-2
0
2
4
6
8
10
12
14
16
quarters after disaster

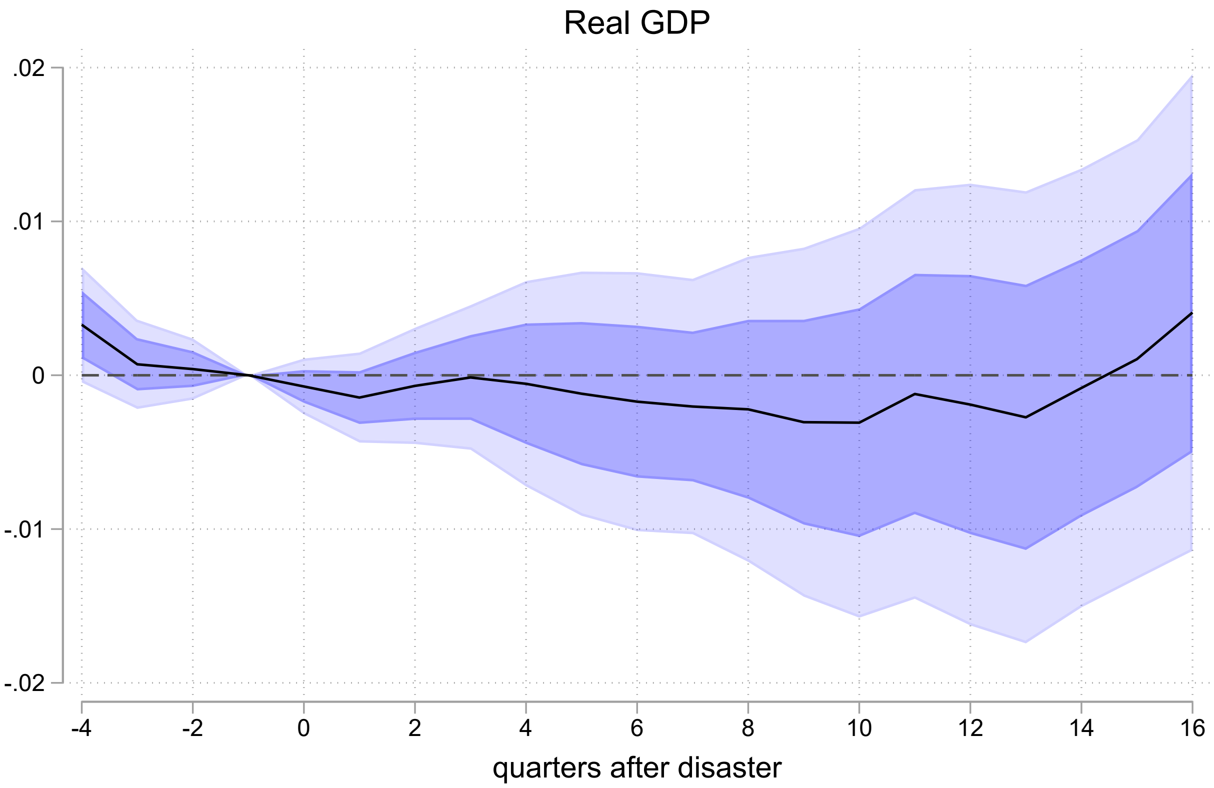


Liquified natural gas prices
.02
.01
0
-.01
-.02
-.03
-4
-2
0
2
4
6
8
10
12
14
16
quarters after disaster


Commercial debt (in p.p.)
.6
.4
.2
0
-.2
-4
-2
0
2
4
6
8
10
12
14
16
quarters after disaster


Consumption debt (in p.p.)
.1
.05
0
-.05
-.1
-4
-2
0
2
4
6
8
10
12
14
16
quarters after disaster


Household debt (in p.p.)
.15
.1
.05
0
-.05
-4
-2
0
2
4
6
8
10
12
14
16
quarters after disaster



Note: shaded areas corresponds to 90 and 68% confidence bands.