Economic consequences of follow-up disasters: lessons from the 2011 Great East
Japan Earthquake

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Abstract

We apply a Bayesian Panel VAR (BPVAR) and DSGE approach to study the regional effects of the 2011 Great East Japan Earthquake. We disentangle the persistent fall in electricity supply following the Fukushima accident, from the immediate but more temporary production shock attributable to the natural disaster. Specifically, we estimate the contribution of the electricity fall on the regions economic recovery. First, we estimate a BPVAR with regional-level data on industrial production, prices, and trade, to obtain impulse responses of the natural disaster shock. We find that all regions experienced a strong and persistent decline in trade, and long-lasting disruptions on production. Inflationary pressures were strong but short-lived. Second, we present a DSGE model that can capture key observations from this empirical model, and provide theoretical impulse response functions that distinguish the immediate earthquake shock from the persistent electricity supply shock. Thirdly, in line with the predictions from the theoretical model, counterfactual analysis via conditional forecasts based on our BPVAR reveals that the Japanese regional economies, particularly the hit regions, did experience a loss in production and trade due to the persistent fall in electricity supply.

Keywords: natural disasters; Bayesian Panel VAR; DSGE; regional spill-overs; counterfactual analysis

JEL codes: E3, E6, Q54, R1

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1   Introduction

The study of natural disasters in macroeconomics deserves scrutiny as the economic damage from such events can have severe regional and even national repercussions that demand from policy makers the right assessment and implementation of fiscal or monetary measures to dampen the blow, and aid recovery. While disasters are often taken as a single event, in reality they tend to be differentiable into multiple events. For instance, an earthquake may cause severe destruction, but may also trigger further distinguishable events that can aggravates the situation, for instance through the outbreak of diseases or, as in Japan, a nuclear accident.

In this article, we introduce the concept of follow-up (natural) disasters to macroeconomic modelling both in empirics and theory. Ideally, the role of a follow-up disaster that is triggered by the first disaster and confounds economic effects with it, would be separately identified for analysis and policy.[1] Specifically for the 2011 Great East Japan Earthquake, the earthquake caused physical damage to the north-eastern coastal regions in Japan, while the nuclear accident at Fukushima triggered a policy response that ordered a complete shutdown of all nuclear power plants in the country, creating a severe negative electricity supply shock.[2]

While natural disasters tend to be rare, they regularly enact a domino of follow-up incidents that can further harm the economy. For instance, in 2017 the destructive force of hurricane Maria affected the power and water supply of Puerto Rico. While the hurricane was first said to have caused just 64 fatalities, this number was questioned and increased after research indicating an excess mortality of several thousand attributable to cuts in water and electricity and the interruption of healthcare services (Kishore et al., 2018). Such secondary effects are also important for lower income economies. For instance, the earthquake in Haiti in 2010, cost a massive amount in lives and physical damage (160,000 fatalities according to Kolbe et al., 2010).[3] The outbreak of cholera ten months later was a second disaster, (arguably) triggered by the first (around 9,000 died in Haiti due to the cholera outbreak, PAHO/WHO, 2017, Alstom, 2016).[4]

On 11 March 2011 and the week that followed it, Japan was struck by multiple disasters.[5] The earthquake and subsequent tsunami had an immediate negative production

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[1] Such follow-up disasters are sometimes called, secondary. However, calling it secondary does not need to imply that the disaster is smaller in magnitude, just that its occurrence was triggered by the one preceding it (Pelling et al., 2002).

[2] This nationwide energy supply shock is what we measure, rather than the more localised effect of the nuclear contamination on land and sea, the loss of economic activity within the evacuation zone, or the spending associated with the clean-up and reconstruction.

[3] An early economic assessment of the Haiti earthquake is provided by Cavallo et al. (2010).

[4] The earthquake destroyed much of the water and sewage system. UN forces from Nepal, who were present as part of a long-established UN peacekeeping force, introduced the cholera bacteria in the country due to unsanitary practices at their base, which were not be mitigated in the post-disaster circumstances.

[5] Further context of the disaster is given in Section 3.2.

effect mainly for one region, Tohoku, but with potential economic spill-overs to the rest of the country. The earthquake directly affected firms in north east Japan, and through input-output supply linkages between firms, it spread across the country (Carvalho et al., 2016). The tsunami in turn impacted the Fukushima nuclear power plant in such way that the reactors experienced an uncontrolled melt-down, causing an explosion and release of highly radio active material in the atmosphere and water. Arguably, the main nationwide economic impact from the nuclear accident came through the subsequent government policy to shut down all nuclear power plants in Japan.[6] In effect, this imposed a substantial negative and persistent supply shock to the Japanese electricity network. Therefore, it is not immediately clear how the economic costs to the Japanese economy can be attributed separately to the regional production shock and the national energy supply shock. We aim to answer this question.

We estimate and model the impact of the disaster and separate the regional production shock from the nation-wide energy process in a within-country regional context. We focus on three key macroeconomic indicators that we observe regionally: industrial production (IP), prices and international trade (through exports and imports). We take a semi-structural approach in three steps. First, we estimate the impact of the combined disaster on Japanese regions using a Bayesian Panel VAR (BPVAR) with data at monthly frequency. The shock, measured through the abnormal deviation of Tohoku IP, will be represented as an exogenous regressor.[7] This approach allows us to estimate impulse responses for IP, prices, imports and exports of the combined disaster that provide insights on the regional heterogeneity of the impact of the combined disaster and recovery process. Second, we set out a DSGE model of a small open economy à la Galí and Monacelli (2005). Our model can approximate the empirical impulse responses from the first step, specifically through general equilibrium economic spill-overs between regions. We extend the model with the inclusion of an electricity supply sector to model an additional transmission channel of the natural disaster to the national level. Therefore, our model gives us a first understanding on the potential impact of the severe and persistent electricity supply shock that followed the shutdown of all nuclear power plants in Japan in response to the nuclear accident. Third, following the assumptions and predictions of the theoretical model, we use an extended version of the BPVAR that applies the theoretical results to the observed data and generate conditional forecasts based on counterfactual paths of the

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[6]In the terminology of Pelling et al. (2002, p. 284), one could say that the earthquake and tsunami are "natural disasters", with the nuclear accident a "technological disaster". In the examples above, the Haiti cholera outbreak, as well as the excess mortality in Puerto Rico may constitute a "deterioration of services". The Fukushima nuclear accident did not cause immediate fatalities. Officially, one death is attributed to the nuclear accident, years after the event itself (BBC News, 5 September 2018, https://www.bbc.co.uk/news/world-asia-45423575). However, the nuclear fall-out affected economically (mostly rural) communities in the direct vicinity of the plant.

[7]"Abnormal deviation" is defined as the difference between observed IP and the 95% confidence boundaries of an hypothetical IP, that is created as a linear combination of IP from other Japanese regions, with coefficients estimated based on a pre-disaster period, see Section 4.

electricity supply. Our goal is to measure the contribution of the electricity process in the recovery of the regional economies by simulating how a disaster without the shortage of electricity supply caused by 'Fukushima' would have looked like in the Japanese context.

Empirical evidence from the BPVAR points to considerable regional heterogeneity in the magnitude of the response to the natural disaster among the included variables. Overall, both hit and non-hit regions experienced a reduction in production, although the effect is much stronger and more persistent in the hit regions. Our findings also show that some regions that were not directly hit by the disaster, such as Hokuriku and Hokkaido, witness an increase in their export activity as a result of the earthquake, indicating a form of export substitution. Inflationary pressures were strong but short-lived. As our theoretical model suggests, the persistent reduction in electricity supply resulted in a more severe decline in local output and trade because of forward looking behaviour of economic agents. A persistent decline in electricity supply in the subsequent future periods reduces the expected income and results in a significant fall in consumption and production in the current period. This effect is stronger in hit regions. The model also suggests that, in the absence of an energy supply shock, regions not directly hit by the earthquake would have experienced a faster and potentially stronger recovery following the negative production shock in the disaster hit regions. The empirical counterfactual is designed to specifically uncover what would have happened if there was no national policy to reduce the nuclear electricity supply, confirms the predictions from the theoretical model. Notably, the Japanese regional economies did experience a loss in industrial production and trade capacity due to the fall in national wide electricity supply that followed the nuclear shutdown. However, our results suggest that the overall contribution to this persistent energy supply shock was minor.

Please see the section headings for the organisation of the remainder of the paper.

2 Literature review

Our paper contributes to the literature that estimates the economic effects on natural disasters in a macro context in four ways. First, Raddatz (2007, 2009) and Fomby et al. (2013) have used Panel VAR methods using cross-country data at the yearly frequency to study the medium and long-run economic outcomes. We estimate our BPVAR using data at the monthly frequency. The higher frequency specifically allows the investigation of short-term adjustments following a natural disaster. Second, one of the underlying assumptions in the before mentioned studies is that a disaster in one country does not affect another. While this maybe a reasonable assumption for cross-country studies, we must explicitly relax it in our within-country regional setting.[8] Microeconomic evidence from

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[8]Nevertheless, there also exist a potential for international spill-overs in policy and economic linkages from natural disasters. Specifically, in the context of the Great East Japan Earthquake, Csereklyei (2014)

the Great East Japan Earthquake indicates that the economic effects propagated through business links (Todo et al., 2015; Cole et al., 2015; Carvalho et al., 2016). Additionally, Hamano and Vermeulen (2020) suggest that the potential of firms to use alternative ports for their trade activity likely aided the resilience of the Japanese economy. Therefore, in our estimation of the contribution of each of the shocks, we must allow for cross-sectional spill-overs. Within this context, and to the best of our knowledge, this is the first study to explore the economic impact of natural disasters using a Bayesian Panel VAR in a regional context on monthly macroeconomic data. Third, while Fomby et al. (2013) and Raddatz (2007) offer empirical evidence on various outcomes and channels through which disasters could affect the economy, we provide a theoretical background for our selection of endogenous variables through a DSGE model that incorporates regional interactions. Fourth, we provide a general equilibrium context to studies that investigate the spatial spillovers in labour markets or trade in a within-country perspective (e.g. McIntosh, 2008; Volpe Martinicus and Blyde, 2013; Hamano and Vermeulen, 2020).

As an alternative to Panel VAR models, some studies used dynamic panel models to estimate the effect of natural disasters on country level macroeconomic outcomes (Ramcharan, 2007; Noy, 2009; Raddatz, 2009; Fratzscher et al., 2020). These have been especially useful to investigate what country characteristics and institutions aggravate or mediate a disaster's economic impact, specifically when concentrating on GDP as the outcome variable. Others, using various univariate estimation techniques and (within) country and time samples, focused on other key economic indicators, such as prices and inflation (Cavallo et al., 2014; Abe et al., 2014; Parker, 2018; Heinen et al., 2018), or trade (Gassebner et al., 2010; Volpe Martinicus and Blyde, 2013; Sytsma, 2020; Hamano and Vermeulen, 2020). Our panel VAR structure explicitly allows each endogenous variable in our system to depend simultaneously on their lags; other endogenous macroeconomic variables of the region; and macroeconomic variables of all other regions.

We also contribute to the theoretical macroeconomic literature of natural disasters. In fact, there is a remarkable lack of theoretical modelling in a DSGE setting that incorporates a natural disaster. To the best of our knowledge, Keen and Pakko (2011) is the only published study. They develop a model to study monetary policy in this context. Our model takes a different benchmark framework as a starting point in order to explicitly incorporate and demonstrate the role of regional interactions in the national propagation of shocks due to natural disasters. However, this does mean that in our analysis we abstract from some other relevant policy aspects of economic adjustment, such as optimal monetary policy, the roles of fiscal transfers (Deryugina, 2017) and labour markets (Belasen and Polachek, 2008) .

Modelling or estimating specifically the effects of a nuclear accident on a macro level

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studies the policy spill-over from the nuclear incident on Germany's decision to close its nuclear plants early, and Boehm et al. (2019) study the effect of the disaster on Japanese subsidiaries in the US.

is not widely attempted. Naturally, and fortunately, this may be due to rarity of such accidents in the past. Before the accident of Fukushima nuclear power plant, only two other major nuclear accidents occurred. The incident at the Three Mile Island nuclear power plant in the US in 1979 and the Soviet-Ukraine Chernobyl disaster in 1986. The main research on the economic consequences of these incidents, including the one in Fukushima, concern risk perception effects on house prices (e.g. Söderqvist, 1995; Tanaka and Managi, 2015; Munro, 2016; Coulomb and Zylberberg, 2016), financial market responses in stocks of energy companies (Bowen et al., 1983; Kalra et al., 1993; Kawashima and Takeda, 2012; Betzer et al., 2013; Lopatta and Kaspereit, 2014), and local effects of economic activity (Tveten et al., 1998; Söderqvist, 2000). The Three Mile Island incident was too small to have larger direct economic effects on regional, let alone national output, while the Chernobyl disaster was extreme in any comparison, but occurred in a non-market economy.[9]

3   Data and methodology

3.1   Road map

Our methodology consists of the following steps. First, we estimate the impact of the exogenous natural disaster shock on the regional economic indicators using a BPVAR. The VAR structure allows our macroeconomic variables to be treated as endogenous. Additionally, the panel dimension is used to estimate heterogeneous responses by region. In this stage, we concentrate on the magnitude of the combined disaster to each region and the path and speed of recovery, without modelling the transmission between regions and through the electricity supply sector.

Second, we are interested in obtaining an estimate of the contribution of the policy to reduce nuclear electricity supply and separate this from the effect of the earthquake and tsunami. We introduce a DSGE model based on Galí and Monacelli (2005) extended in a multi-region economy and with energy in the production function. This model reasonably approximates the direction of responses and the regional heterogeneity that are estimated in the first step. Additionally, the inclusion of the electricity supply sector, allows to uncover the potential impact of the severe and persistent electricity supply shock in response to the nuclear accident.

Finally, we return to our data and conduct conditional forecasts with an extended version of the BPVAR framework that incorporates the assumptions from the theoretical model, i.e. introducing the electricity supply sector and allowing for interactions and

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[9]Analyses of the Chernobyl disaster using non-stochastic Computable General equilibrium (CGE) models based on input-output modelling have been conducted as PhD dissertations (Yevdokimov, 1998; Konovalchuk, 2006). Okuyama (2007) reviews developments in modelling disasters in non-stochastic CGE and input-output models.

spillovers among regions. Our scenario analysis models regional electricity supply based on its pre-crisis trend, in order to measure how a natural disaster would have looked like in the Japanese context without a shortage of the electricity supply due to the accident at the Fukushima nuclear power plant.

3.2 Context

On 11 March 2011, an earthquake of magnitude 9 at the Richter scale struck 70 km off the north eastern coast of Japan at depth of 70 km, and was followed by dozens of 'smaller' earthquakes of magnitude 6 and higher. The earthquake caused a tsunami to hit the coast. Multiple waves hit the shore of north eastern Honshu (Tohoku) with heights up to 6 meters from sea level, see Figure 1. The force of the wave made the water surge inland as much as 40 meters above sea level, and in some areas a few kilometres from the coast, albeit these were local extremes.[10] The flooding caused major damage along coastline where many cities and ports are located. Most prominently, it caused the flooding of a nuclear power plant at Fukushima, which subsequently malfunctioned, partly exploded and released nuclear radiation in the air and water (Hayashi, 2012). Immediate government aid and reconstruction helped to normalise a large part of the hit area. A majority of business opened within two weeks (Todo et al., 2015; Cole et al., 2015). Seaports located directly in the line of the tsunami took much longer to recover, which hampered international trade links (Ono et al., 2016; Hamano and Vermeulen, 2020). The Fukushima disaster had major repercussions for the entire country. All nuclear plants in Japan were ordered to shutdown, which happened gradually. This in turn caused a major electricity supply disruption across the country. However, nuclear power was eventually replaced with power from other sources, such as imported natural gas.

3.3 Data

We collect data from public sources released by various Japanese (semi-)public organisations. At the monthly-regional level we have access to: industrial production index (IP), prices, electricity supply by power source, exports and imports of merchandise goods.[11] We also observe the monetary policy rate.[12]

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[10]Some researchers have been able to differentiate between the effects of the earthquake and the tsunami due to geographical nature of the impact using micro-data (Cole et al., 2015; Carvalho et al., 2016).

[11]The sources are as follows. IP: Japan Ministry of Economy, Trade and Industry, available at `http://www.meti.go.jp/statistics/tyo/iip/chiiki/index.html`; Prices: Official Statistics of Japan, `https://www.e-stat.go.jp/stat-search/files?page=1&layout=datalist&toukei=00200573&tstat=000001084976&cycle=0&tclass1=000001085995&tclass2=000001085937`; Electricity supply: Japan Ministry of Economy, Trade and Industry, available at `http://www.enecho.meti.go.jp/statistics/total_energy/`; international trade: Japan Ministry of Finance, Trade Statistics, available at `http://www.customs.go.jp/toukei/info/tsdl_e.htm`.

[12]Federal Reserve Bank of St. Louis, `https://fred.stlouisfed.org/search?st=Japan+real+exchange+rate`.

Figure 1: Japan regions and the 2011 Great East Japan Earthquake
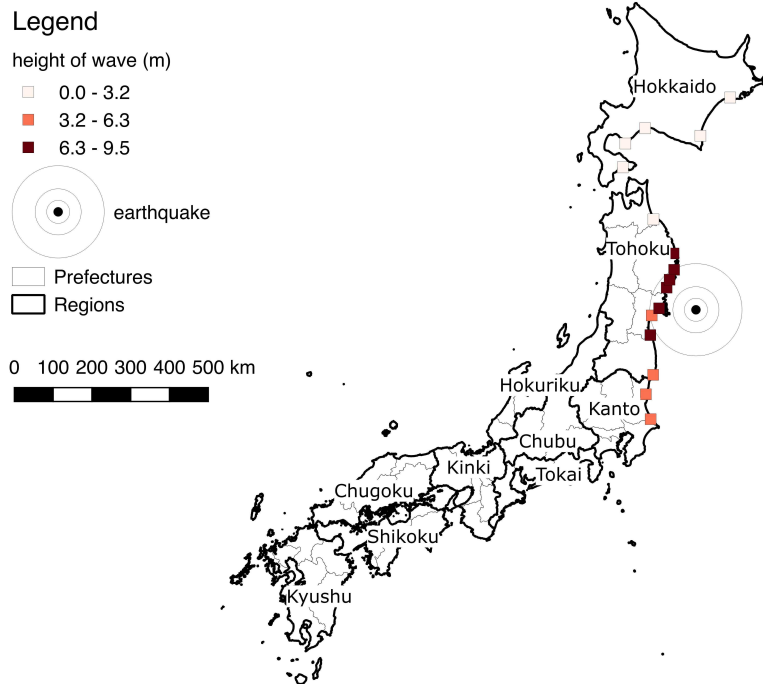
The shaded squares indicate the measured maximum wave height at these specific points, which are sea ports (Ministry of Land, Infrastructure and Transport, 2011). The indicated location of the epicentre of the largest earthquake is from the US Geological Survey (2011) (http://earthquake.usgs.gov/earthquakes/browse/significant.php).

Figure 2 presents the main endogenous regional data series that we incorporate in our BPVAR, for the period April 2008 to March 2014. The impact of the earthquake is clearly visible for Tohoku in terms of IP and trade. For Kanto, we can observe some effect in IP but not in trade. All regions demonstrate a similar boost in inflation, but this does not seem to be timed with the disaster. The electricity supply is combined from all energy sources, including nuclear power. The data has been cyclically adjusted using the mean for each month over all years. A persistent reduction for Tohoku and Kanto is noticeable in the bottom left panel.

Figure 3 indicates descriptive variables of the exogenous processes that affected the Japanese economy; the earthquake and nuclear power supply by region. The earthquake series are obtained from the US Geological survey world wide database on earthquake events, limited to those with epicentres within 100km of Japanese landmass and less than 70km deep, whereafter we associated the epicentres to the closest Japanese region using geospatial tools.[13] The top-left figure clearly indicates that Tohoku experienced a large number of major earthquakes over several months. The Kanto region experienced also some of these, but the other regions did not. It reveals that the exogenous earthquake shock was sudden, but it also has some persistence.
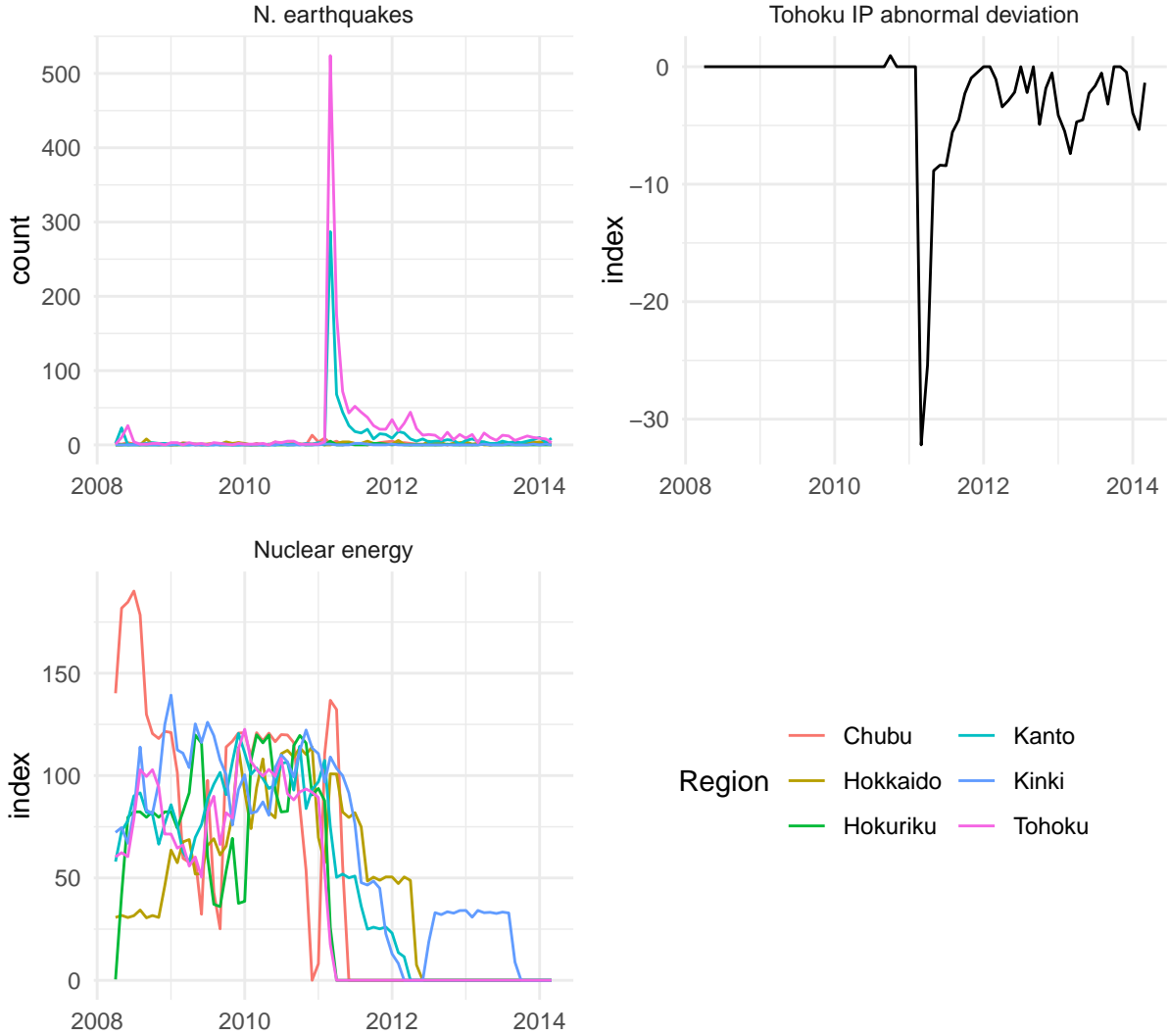
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[13]United States Geological Survey, available at https://earthquake.usgs.gov/earthquakes/search/, downloaded on 23 April 2018.

Figure 2: Endogenous variables
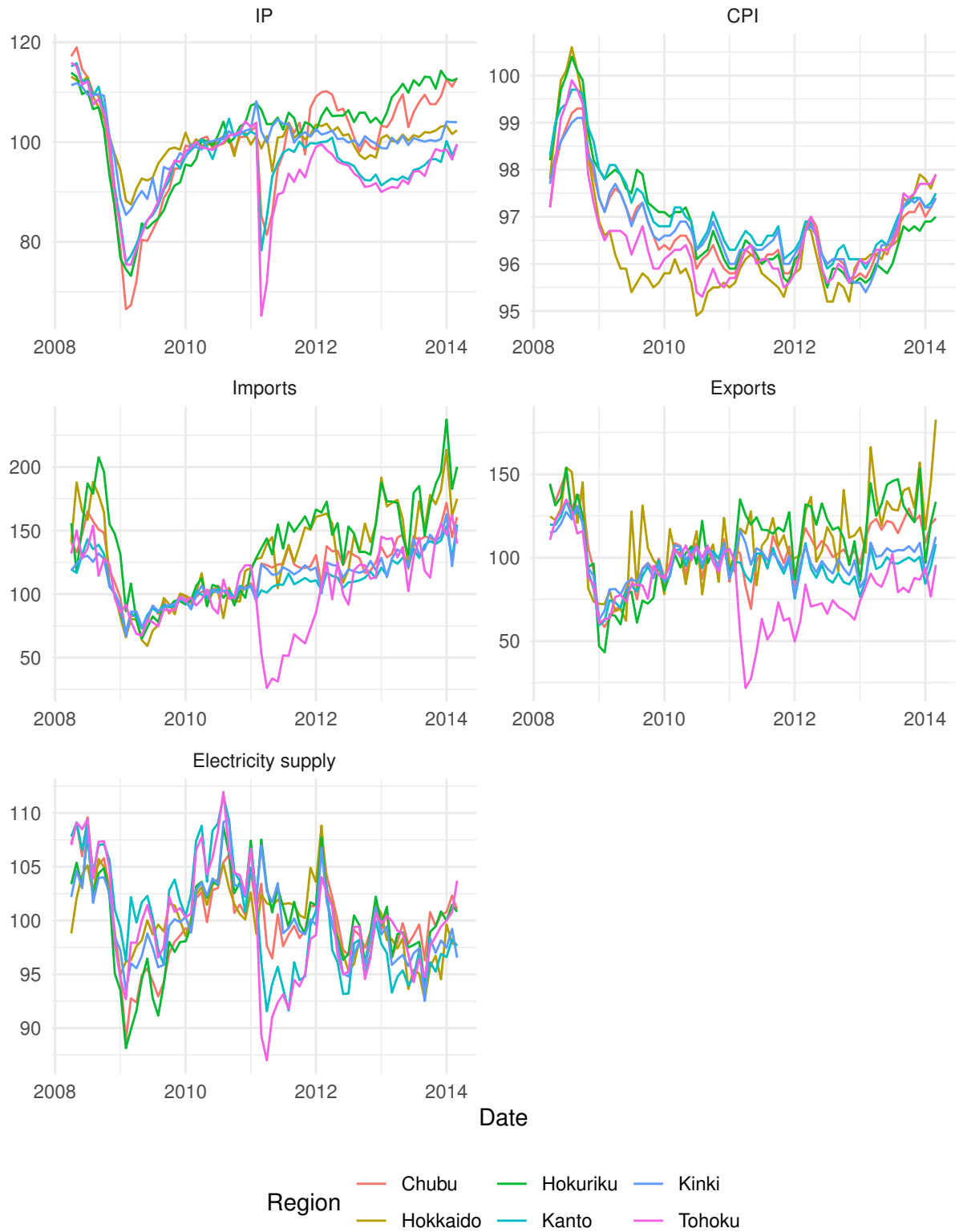
Data sources are given in the text. All series are represented as indices, for prices: 2015=100; for trade: 2010=100; for IP: 2010=100.

Figure 3: Follow-up shocks to the Japan economy

Data sources are given in the main text. 'N. earthquakes', indicates the number of 'larger' earthquakes by month for each region. Nuclear energy presents index values of nuclear energy supply for each by region (2010=100). For the Tohoku IP abnormal deviation the measure are index points differences between observed and a predicted value.

To obtain a more direct measure of the economic effect of the earthquake and tsunami on the most affected region, we calculate a measure of Tohoku's abnormal IP deviation.[14]

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[14]This variable is different from measures commonly found in the literature, such as the estimated (direct) damage variable in money terms (Noy, 2009; Cavallo and Noy, 2011; Fratzscher et al., 2020), or number of people affected (Fomby et al., 2013). Our variable approximates the indirect damage from forgone economic activity. We do this for two reasons. Firstly, given that we focus on a single event, and in contrast to papers studying multiple disasters over time and countries, we require a little more information on the shock over time to identify the coefficients in the system, rather than the (estimated) capital damage at the time of impact. The estimated excess under-production in Tohoku aims to capture the aggregate exogenous effect over time on industrial activity relative to other Japanese regions Secondly, a harmonised estimated measure of damage value is useful for analysis across many disaster events (e.g. at the global cross-country level), but we do not need this. See Kajitani and Tatano (2014) for an alternative methodology of estimating production loss based on more fundamental data.

Table 1: Pre-disaster monthly nuclear supply (April 2008 - February 2011)

region	mean	min	max
Chubu	12.4	0.0	22.4
Chugoku	9.6	0.0	20.4
Hokkaido	32.6	14.1	56.1
Hokuriku	34.4	0.2	60.5
Kanto	24.8	17.2	34.0
Kinki	40.9	27.5	58.7
Kyushu	41.5	32.1	53.3
Okinawa	0.0	0.0	0.0
Shikoku	47.0	28.1	62.6
Tohoku	22.9	13.7	30.8
Total	27.2	22.8	32.1

Figures are the percentage of total electricity supply.
Source: author calculations based on `http://www.enecho.meti.go.jp/statistics/total_energy/`

We regress Tohoku IP on the IP of Hokkaido, Kinki and Shikoku using the sample period January 2008 to March 2011. Using the estimated model we predict the rest of the period (up to March 2014), with 95% confidence band. The Tohoku abnormal IP deviation is then defined as the distance of observed Tohoku IP from the predicted band. The resulting series is presented in the top-right panel of Figure 3.

To demonstrate where the potential variation from total electricity supply in Figure 2 originates from, we present in the bottom-left panel of Figure 3 the index of nuclear energy supply (2010=100, no cyclical adjustment). It is generally volatile over time, due to occasional (planned maintenance) shutdowns of individual plants. However, after 2011 the general decline in nuclear supply is clearly noticeable. Nuclear energy presents an important share of Japans' electricity supply mix. Table 1 presents the mean, minimum and maximum share of monthly nuclear energy of a region's total energy supply over the period from April 2008 to February 2011. The supply varies considerably, with the lowest mean value for the regions that we concentrate on in Chubu (12.4% of total) and the largest for Kinki (40.9). Nonetheless, the effect in total energy supply, as indicated in Figure 2, is not as strong since the loss of nuclear energy can partly be absorbed by other sources.[15]

4 Bayesian Panel VAR

Panel VARs are widely used in the context of macroeconomic (mainly) and microeconomic analysis. For example, in macroeconomics, Panel VARs have been used to study

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[15]Japan has two major electricity regions, one based on 50 Hz in east Japan and 60 Hz in West Japan. Within these regions electricity flows freely, but not between. However, the policy of shutting down nuclear powerplants was nation wide, and so affected all regions, independent of their electricity frequency.

fiscal multipliers (Ilzetzki et al., 2013; Corsetti et al., 2012), the transmission of monetary policy shocks (Jarocinski, 2010; Goodhart and Hofmann, 2008) and also external shocks to macroeconomic aggregates across countries (Canova, 2005; Raddatz, 2007). In microeconomics, Panel VARs have been used to examine the dynamics of earnings and hours worked among workers (Vidangos, 2009) and financial development and firm behaviour (Love and Zicchino, 2006).[16]

Our Panel VAR is perfectly suitable to be applied to the analysis of a natural disaster for the following reasons. First, in contrast to univariate and panel data models, the Panel VAR provides rich information on specific sources of variation that are important for our analysis. Specifically, crucial for understanding the regional effects of disasters is to measure the dynamic effects of natural disasters in each of the variables in the system and each of the regions. Second, this framework allows us to investigate the contribution of disasters shocks to short-run and medium-run movements in macroeconomic variables, thus, providing a good insight on the regional heterogeneity of the impact and recovery. Third, we can incorporate regional interaction and spill-overs into our Panel VAR.

Furthermore, the VAR dimension of the BPVAR allows for all economic indicators to be endogenous to the system. In addition, we allow the VAR coefficients and residual variances to be region-specific, i.e. we introduce cross-regional heterogeneity. Finally, we incorporate exogenous variables.

The focus of the analysis in this section is the impact of a common exogenous natural disaster shock and the estimation of the aggregate effect of the natural disaster on the regional economies, rather than the origin of the cross-sectional spillovers. Therefore, we start with a model that assumes no dynamic interdependencies between regions and without disentangling a production effect from an energy supply effect. We capture the external shock through the abnormal deviation of Tohoku IP and estimate the response for each regions' endogenous variables. Below, we provide a summary description of the estimation method. A detailed description of the estimation is provided in Appendix A.1.[17]

Traditional VARs estimated either by least squares or maximum likelihood, often require many lags to improve the in-sample fit, leading to a significant loss of degrees of freedom and thus to poor forecasts. Bayesian shrinkage, which is obtained by a prior that concentrates more around zero for higher lags, allows us to reduce the number of lags, hence, limiting the over-parameterisation issue. Moreover, the length of the data-span in our case, as will be demonstrated below, is rather short for the number of parameters

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[16]For an in-depth survey of Panel VAR applications see Canova and Ciccarelli (2013).

[17]Bayesian Panel VARs are estimated by using the BEAR toolbox of Dieppe et al., 2016. A similar Panel VAR approach was adopted by Ciccarelli et al. (2013) who analyse how financial fragility has affected the transmission mechanism of the single Euro area monetary policy during the crisis until the end of 2011 and Jarocinski (2010), who provides systematic comparisons of impulse responses to monetary shocks in the euro area countries before the EMU and in the New Member States from central and eastern Europe.

that we aim to estimate. As a consequence, estimation of objects of interest for this paper such as, impulse responses and forecasts, can become imprecise. By supplying prior information into the estimation, we obtain estimates which are generally more precise than those obtained using traditional methods, thus compensating for the short sample. Last, Bayesian simulation methods, such as Gibbs sampling that we use in this paper, provide an efficient way to obtain point estimates and to characterise the uncertainty around those point estimates by obtaining confidence bands.

The general form of the BPVAR model for region $i = 1, \ldots, N$ at time t is given by

$$y_{i,t} = A_i^1 y_{i,t-1} + \cdots + A_i^p y_{i,t-p} + C_{i,t} x_t + \varepsilon_{i,t}, \tag{1}$$

where $y_{i,t}$ denotes a $n \times 1$ vector of n endogenous variables of region i at time t, A_i^p is a $n \times n$ matrix of coefficients, x_t is the $m \times 1$ vector of exogenous variables, $C_{i,t}$ is the $n \times n$ matrix connecting the endogenous to the exogenous variables, and $\varepsilon_{i,t}$ denotes a $n \times 1$ vector of residuals with $\varepsilon_{i,t} \sim N(0, \Sigma)$, where Σ is a diagonal matrix with Σ_i elements in the diagonal. In our estimations the number of lags of the endogenous variables, p, is four. By transposing (1), writing in compact form and stacking over T sample periods, we get

$$Y_i = X_i B_i + e_i, \tag{2}$$

$$\text{where } Y_i = \begin{bmatrix} y_{i,1} \\ \vdots \\ y_{i,T} \end{bmatrix}, X_i = \begin{bmatrix} y_{i,0}' & \cdots & y_{i,1-p}' & x_i' \\ \vdots & \ddots & \vdots & \vdots \\ y_{i,T-1}' & \cdots & y_{i,T-p}' & x_T \end{bmatrix}, B_i = \begin{bmatrix} A_i^1 \\ \vdots \\ A_i^p \\ C_i' \end{bmatrix}, e_i = \begin{bmatrix} e_{i,1}' \\ \vdots \\ e_{i,T}' \end{bmatrix}.$$

This reformulates in vectorised form as,

$$y_i = \bar{X}_i \beta_i + \varepsilon_i, \tag{3}$$

where $y_i = vec(Y_i)$, $X_i = I_n \otimes X_i$, $\beta_i = vec(B_i)$ and $\varepsilon_i = vec(e_i)$. Note that $\varepsilon_{i,t}$ now takes the following form, $\varepsilon_{i,t} \sim N(0, \Sigma_i \otimes I_t)$.

Next, we introduce cross-sectional heterogeneity, essentially allowing our model to replicate regional specific VARs. We implement this by assuming that for each region i, β_i can be expressed as $\beta_i = b + b_i$, with b being a $n \times 1$ vector of parameters and $b_i \sim N(0, \Sigma_b)$. It follows that $\beta_i \sim N(b, \Sigma_b)$, which implies that the Panel VAR coefficients will differ across regions, but they are drawn from a normal distribution with a constant mean and variance. We estimate the model using Bayesian techniques. We follow the hierarchical prior approach of Jarocinski (2010) to derive the posterior distributions of our model parameters.

To identify the BPVAR model correctly and allow for meaningful interpretation of

the impulse responses we adopt the following strategies. First, as already mentioned, we identify the impact of earthquake events as an exogenous variable. This strategy implies that the earthquake shock affects all the macroeconomic variables in the system and across regions, contemporaneously, but none of them is allowed to affect the earthquake variable.

Second, the block of endogenous, regional variables is identified through Cholesky decomposition. Specifically for our case, IP is ordered first, followed by CPI inflation and last, the trade variables (imports and exports).[18] The identification strategy implies that a shock to the regional IP has a contemporaneous effect on all other domestic variables in the region, but none of them can affect the regional IP, except through the exogenously defined earthquake shock. Similarly, a shock to the regional CPI inflation impacts all the other variables within the region apart from IP, but only the exogenous earthquake shock and regional IP can affect prices contemporaneously.

Producing impulse responses with the BPVAR model is aided by the imposed structure as the model ultimately results in the estimation of a set of N independent VAR models, one for each region. Moreover, the Bayesian framework that we adopt makes it possible to integrate the impulse responses calculation into the Gibbs sampling framework that is set out in Appendix A.1.3. In particular, to calculate the impulse responses functions, we obtain the predictive distribution $f(y_{t+1:t+h} \mid y_t)$ where h is the forecasting period.

4.1 Evidence from Bayesian Panel VAR

Figure 4 shows the responses of the four endogenous variables to an exogenous earthquake shock in Tohoku in all six regions for horizons up to sixteen months. For exposition we divided the responses by the two regions closest to the epicentre of the earthquake (hit) and four regions further away (non-hit). We did not impose this categorisation in the estimation. The dots on the lines indicate that the 68% confidence interval does not encompass zero.

Industrial production Broadly speaking, the findings point to considerable heterogeneity in the impact of earthquakes on different sectors of the economy, across regions. The starting point is industrial production (IP). The figures show that in response to earthquake shocks, there is a substantial and persistent decline in IP for three out of four non-hit regions, Chubu, Kinki (Kansai), Hokuriko, and both hit regions, Kanto and Tohoku. Chubu appears to be affected due to its regional proximity to Kanto. There is heterogeneity in the size of the effect between these regions. Moreover, the shock has a persistent effect, as the adjustment towards zero takes about 12 months. The response of Hokkaido is the smallest and statistically indistinguishable from zero, indicating a level
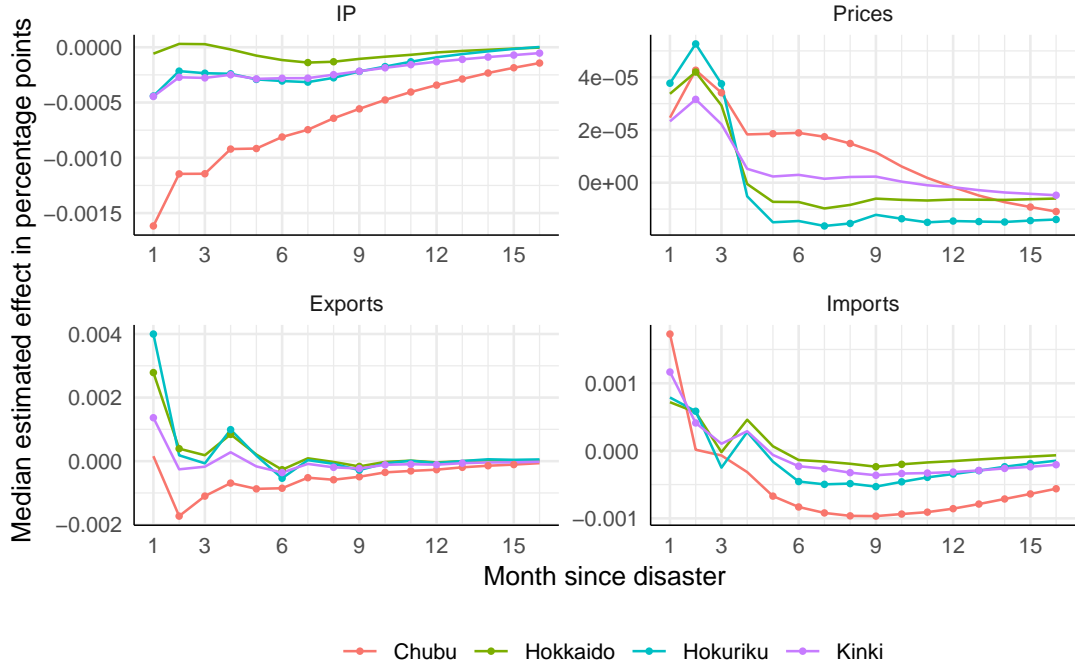
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[18]The ordering of the variables that we use in this paper follows the broader literature of VAR modelling in a macroeconomic context (e.g. Eichenbaum and Evans, 1995; Christiano et al., 1999).

Figure 4: BPVAR, impulse responses to Tohoku IP abnormal deviation.
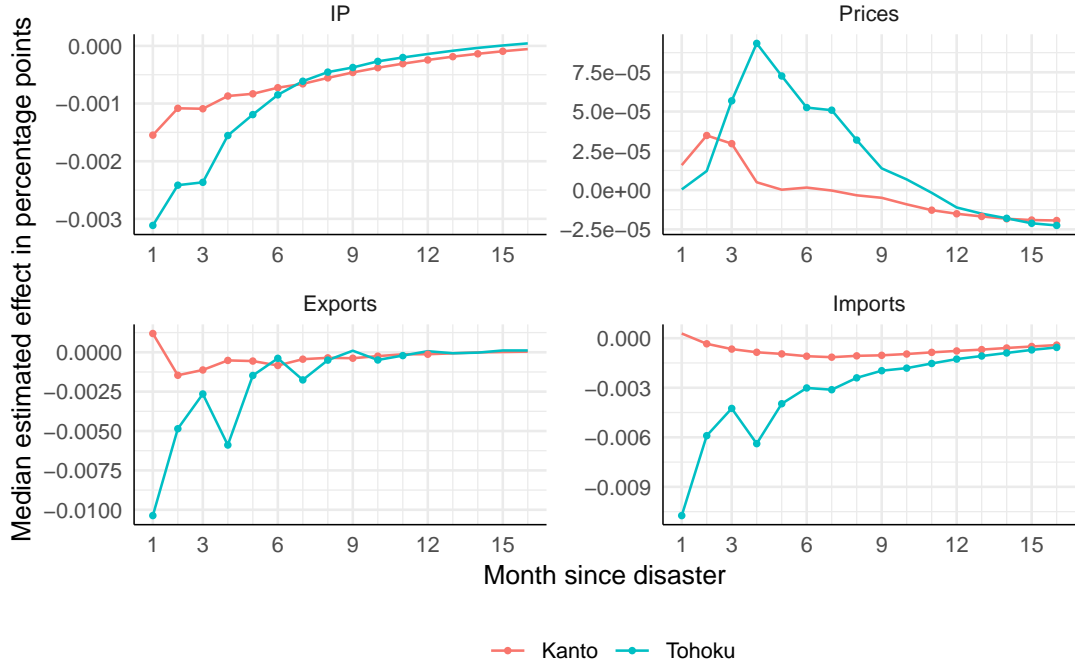
Note: Impulse responses from BPVAR estimation. Lines indicate monthly median impulse responses of each variable to a one standard deviation shock of Tohoku IP abnormal deviation To avoid overlapping confidence bands, the dots at a line indicate statistical significance at 68% level. The two regions closest to the epicentre of the earthquake are named hit, and the four regions further away non-hit. This categorisation was imposed during the estimation.

of regional isolation of the northern main island. Overall, the significant decline of IP observed in the majority of regions is consistent with the micro-evidence of disruption from domestic supplier linkages for those firms that had links with firms in the earthquake hit region (Carvalho et al., 2016).

Prices In relation to prices, all regions exhibit a strong positive increase in the first months after the shock. What is also common to all regions is that, the responses are short lived as they very quickly become statistically insignificant. The only exceptions are the hit region of Tohoku and non-hit region of Chubu for which inflationary pressures are more persistent. The positive but relative limited response in prices is consistent with a more detailed analysis of Cavallo et al. (2014) and Abe et al. (2014), who study detailed retail prices and purchase behaviour around the time of 2011 disaster, and the analysis of Parker (2018) encompassing cross-country data and many different types of disasters.

Exports Regarding exports, Tohoku, Kanto and Chubu, are strongly affected as indicated by the substantial decline of the responses immediately after the shock. In all three cases, the rapid initial fall slowly dissipates; this is evidence that the impact of earthquake on exports is not temporary. The response of exports for Kinki rises on impact, but this initial increase is rapidly reversed as evidenced by a decline into negative territory. The response is smaller in magnitude, compared with the other three regions, and quicker to revert to zero levels. On the contrary, Hokuriku and Hokkaido witness an increase in their exports as a result of the shock, indicating a form of export substitution (Hamano and Vermeulen, 2020). This rise, in both cases, lasts for approximately five months; thereafter, the responses become insignificant.

Imports Tohoku's response points to a significant drop in imports. Imports for Chubu, Kinki and Kanto (to a lesser extent) exhibit a sudden and temporary hike, which afterward becomes negligible. Responses for Hokuriku and Hokkaido are statistically insignificant, which provides additional evidence in favour of the hypothesis that the impact of the earthquakes in these two regions, compared with the impact in the other four regions, is rather modest.

The analysis in this section demonstrated the direct impact of earthquakes on the economies of various regions, notably Chubu, Kanto, Kinki and Tohoku. As a result of the disaster, all these regions experienced a strong and persistent decline in trade, as indicated by the fall in exports and also, long-lasting disruptions on production. Inflationary pressures were strong but short-lived.

These responses are the result of the combined immediate impact of the earthquake and tsunami and the nation-wide shutdown of all nuclear energy plants. Therefore, a natural question to ask is whether it is possible to disentangle the impact of these two

distinct shocks on the economy. We do this in two steps. First, we set out a DSGE model that can broadly replicate the above responses through regional interactions and separate the effects between those of the production shock from the natural disaster and the reduction in energy supply. Secondly, guided by this theoretical model, we estimate the impact of nuclear plant shutdown by adding the total energy supply component in an extended form of BPVAR that accommodates interactions among regions and we use this empirical model to build counterfactuals for policy analysis.

5   Theoretical Model

We develop a small open economy theoretical framework with price rigidity that features heterogeneous regional economies and allows us to further explore some of our results.

We prefer the model to be tractable and intuitive, potentially at the cost of being stylised and not suitable for a detailed calibration of the Japanese economy. Therefore, we extend Galí and Monacelli (2005) to include a continuum of small openeconomies with an energy sector. Our objective is three-fold: we aim to explore the impact of a regional productivity shock, provide a mechanism through which regional productivity shocks impact the nation wide energy supply, and investigate how aggregate output shocks may affect individual, non-hit regions. In particular, each region, functioning as a small open economy, is subject to one of the following exogenous shocks: either a region specific productivity shock, which refers to the impact of a shock that is generated in the hit region or, an aggregate output shock which approximates a shock that takes place outside the region. In the theoretical model, in line with the BPVAR in the previous section, we consider Tohoku and Kanto as the regional economies that were hit directly by a region specific productivity shock. Chubu and Kinki are treated as the non-hit regions that were indirectly affected by an aggregate output shock.

We present the model focusing on the changes with respect to Galí and Monacelli (2005) and relegate the details of the model to Appendix B. Throughout the presentation, variables represent those of individual regions that function as small open economies, while the variables with $*$ stand for the rest of the world which is outside of the small open economy.

5.1   Households

Within a country, there is a continuum number of atomistic regions, which is indexed by i in unit interval. The representative household in a generic region maximises the expected inter-temporal utility with respect to nominal consumption and labor supply.

The basket of goods C_t is defined as

$$C_t = \left[(1-\alpha)^{\frac{1}{\eta}} C_{H,t}^{\frac{\eta-1}{\eta}} + \alpha^{\frac{1}{\eta}} C_{F,t}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \tag{4}$$

where α is the demand attached to the bundle of goods produced in other regions $C_{F,t}$, $\eta\,(>0)$ denotes the elasticity of substitution between locally produced goods in Home region $(C_{H,t})$ and imported goods from Foreign region $(C_{F,t})$. Further, imported goods $C_{F,t}$ are composed from imperfectly substituted goods from each region $C_{i,t}$. The basket of locally produced goods $C_{H,t}$ is also composed from imperfectly differentiated goods $C_{i,t}(j)$ which is produced by firm j within region. We assume that the elasticity of substitution across products within the same region i is higher than η.

5.2 Production

There is a continuum of firms within a unit interval in each region. Firms are monopolistically competitive and produce one product variety, which is imperfectly differentiated. Production requires energy as well as labor. The production function of a particular final good j is thus given by

$$Y_t(j) = A_t N_t^{\mu}(j) \left(\mathfrak{E}_t(j) \right)^{1-\mu},$$

where A_t is total factor productivity, $N_t(j)$ stands for labor used in final good sector, and $\mathfrak{E}_t(j)$ represents energy as intermediate inputs whose price is $P_{e,t}$.

The cost minimisation yields the optimal demand for each factor of production. The optimal labour and energy demand is found to be respectively

$$N_{f,t}(j) = \left(\frac{W_t}{MC_t} \right)^{-1} \mu Y_t(j), \quad \mathfrak{E}_t(j) = \left(\frac{P_{e,t}}{MC_t} \right)^{-1} (1-\mu) Y_t(j), \tag{5}$$

where W_t stands for nominal wages. In the above expressions, nominal marginal cost MC_t is defined as

$$MC_t \equiv A_t^{-1} \left(\frac{W_t}{\mu} \right)^{\mu} \left(\frac{P_{e,t}}{1-\mu} \right)^{1-\mu}. \tag{6}$$

The firm sets the price knowing the demand it faces. The price is assumed to be sticky à la Calvo (1983) and only a fraction $1-\theta$ of firms can re-optimise their prices.[19]

5.3 Interregional Financial Market and General Equilibrium

Financial markets are assumed to be complete, implying the perfect *inter-regional* consumption risk sharing. Complete financial markets allow households to insure perfectly for consumption risk arising from disasters. As a result of the inter-regional lendings and

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[19]Cavallo et al. (2014) mention limited price updating of firms around disasters. This would be an important observation that need to be addressed. However, we do not model a specific pricing behaviour at the timing of the disaster and stick to a standard staggered price setting framework in our analysis.

borrowings, trade is not balanced.[20] The model is completed by considering two market clearing conditions. First, the goods markets clears for a typical good j with

$$Y_t(j) = C_{H,t}(j) + \int_0^1 C_{H,t}^i(j)di.$$

Second, denoting the national energy supply with $\mathfrak{E}_t^*$, energy market clears as $\mathfrak{E}_t^* = \int_0^1 \int_0^1 \mathfrak{E}_t^i(j)djdi$. Plugging the energy demand found previously, we can further rewrite the energy market clearing condition as[21]

$$\mathfrak{E}_t^* = \left(\frac{1-\mu}{\mu}\right)^\mu Y_t^* A_t^* \left(\frac{W_t^*}{P_{e,t}}\right)^\mu, \tag{7}$$

where we define the output in other regions and technology level in other regions as $Y_t^* \equiv \int_0^1 Y_t^i di$ and $A_t^* \equiv \int_0^1 A_t^i di = 1$. Note that energy circulates freely within the country without any cost implying that energy price is the same across regions, i.e., $P_{e,t}^i = P_{e,t} = P_{e,t}^*$. Workers are assumed to be mobile across regions implying that $W_t^* \equiv \int_0^1 W_t^i di = W_t$.

We assume the following process for A_t, $\mathfrak{E}_t^*$ and Y_t^*,

$$\begin{pmatrix} \ln A_t \\ \ln \mathfrak{E}_t^* \\ \ln Y_t^* \end{pmatrix} = \begin{pmatrix} \rho_a & 0 & 0 \\ 0 & \rho_{e^*} & 0 \\ 0 & 0 & \rho_{y^*} \end{pmatrix} \begin{pmatrix} \ln A_{t-1} \\ \ln \mathfrak{E}_{t-1}^* \\ \ln Y_{t-1}^* \end{pmatrix} + \begin{pmatrix} \varepsilon_{a,t} \\ \varepsilon_{e^*,t} \\ \varepsilon_{y^*,t} \end{pmatrix}$$

where ρ_a, ρ_{e^*} and ρ_{y^*} stand for the persistence of each shock. The errors $\varepsilon_{a,t}$ and $\varepsilon_{y^*,t}$ are i.i.d. innovations. We assume that innovation on total electricity supply $\varepsilon_{e^*,t}$ is perfectly correlated with either $\varepsilon_{a,t}$ or $\varepsilon_{y^*,t}$.

Finally, the interest rate on nominal bonds, r_t, is risk free and controlled by the central bank following a simple Taylor rule such that $r_t = \phi_P \pi_t^*$ where π_t^* stands for nationwide inflation rate and ϕ_P is the reaction of the central bank with respect to the inflation in setting the risk free rate r_t.[22]

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[20]For each region which is defined as a small open economy, there is no distinction between regional trade and international trade. See Appendix for the definition of net export, export and import.

[21]Putting the energy demand found in (5) and the expression of the marginal cost (6), we have

$$\mathfrak{E}_t^* = \int_0^1 \int_0^1 \mathfrak{E}_t^i(j)djdi = \int_0^1 \int_0^1 \left(\frac{P_{e,t}^i}{MC_t^i}\right)^{-1} (1-\mu) Y_t^i(j)djdi$$

$$= (1-\mu) Y_t^* \int_0^1 \left(\frac{P_{e,t}^i}{MC_t^i}\right)^{-1} di = \left(\frac{1-\mu}{\mu}\right)^\mu Y_t^* \int_0^1 A_t^i \left(\frac{W_t^i}{P_{e,t}^i}\right)^\mu di.$$

Finally plugging the definition of aggregate output and technology as well as wage equality across regions, we get (7).

[22]We introduce monetary policy rate without considering zero lower bound. As we will see, this is not problematic given our specific Taylor rule that produces interest rate hike following inflationary disaster shock. Our focus in the paper is to see the inflation dynamics and output contraction following the disasters and not the way of conduct of monetary policy that potentially could mitigate the impact, which is of course an interesting topic for future research (e.g. Keen and Pakko, 2011).

The whole (log-linear) system is summarised in Table B-1 in the appendix.

5.4 Calibration

We calibrate the model with parameter values at monthly basis in Table B-2 in the Appendix. The parameter values of preferences and elasticities are taken from Galí and Monacelli (2005). We set the Calvo price setting probability as $\theta = 0.92$ which is consistent with a price duration of 12 months as is standard in the literature. Electricity consumption demand in total energy in Japan was around 25.4% in 2010 (among which nuclear generated electricity accounted for 27.2%. See Table 1).[23] Fujiwara et al. (2005) estimates the share of capital in Japanese economy as 37 %. Given these numbers, we set the share of electricity in production as $1 - \mu = 0.254 \times 0.37 = 9.4\%$.

Following the analysis of our BPVAR, we aim to show qualitatively the impulse responses of hit and non-hit regions. In particular, we produce the responses of the hit-regions by assuming a persistent reduction in energy supply $\mathfrak{E}_t^*$ that is induced by a 1 % negative standard deviation shock on log of regional productivity ($\varepsilon_{a,t} = 1$ and $\varepsilon_{e^*,t} = \varepsilon_{a,t}$). On the other hand, the responses of the non-hit regions are produced as the result of a persistent reduction in energy supply $\mathfrak{E}_t^*$ caused by a 1% negative standard deviation shock on log of output in the other regions ($\varepsilon_{y^*,t} = 1$ and $\varepsilon_{e^*,t} = \varepsilon_{y^*,t}$). In the calibration, we set $\rho_a = \rho_{y^*} = 0.1$ and $\rho_{e^*} = 0.9$ to capture a relatively short-lived impact of productivity and output shock in contrast with the persistent energy supply shock.

5.5 Impulse Response Functions

Figure 5 shows the impulse responses of our model.[24] Figure 5(a) presents the responses of the hit regions, following a 1% negative standard deviation shock on regional productivity $\varepsilon_{a,t}$. The green solid lines show the responses under the benchmark calibration. In line with our BPVAR, local output, exports and imports decrease on impact and remain persistently low for several months, before returning to their initial steady state level. This contraction in capacity is responsible for the inflation spikes on impact. Again, consistent with our BPVAR, the latter effect quickly decays after a few months. Turning to Figure 5(b), a negative output shock in other regions, $\varepsilon_{y^*,t}$, causes the local, non-hit economy to contract on impact, as evidenced by the fall in output, exports and imports, followed by an immediate inflation spike. However, note that six months after the shock, output, exports and imports recover quickly and even strongly increase. The positive

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[23]Japans electricity consumption as a share of total energy consumption in 2010 was 3.73 exajoules/14.71 exajoules=0.254 (Statista, 2020, https://www.statista.com/statistics/868332/japan-electricity-consumption/ , https://www.statista.com/statistics/868275/japan-final-energy-consumption/).

[24]Appendix B.4 provides the IRFs of the other variables.

boost in the real economy variables is due to the substitution of other regions' economic activities.

Overall, our model approximates well, at least qualitatively, the direction of the responses for each variable and the heterogeneity by region. A positive deviation of IP for non-hit regions was not observed empirically, which is not unexpected given that the empirical model cannot explicitly capture substitution effects between locally produced goods and imported goods from foreign regions. However, generally we observe a similar pattern for both hit and non-hit regions as in Figure 4. The signs of the responses of IP and trade variables for the hit regions from the BPVAR are in line with their respective responses from the theory. Price responses are positive in the theory and data for both types of regions. Furthermore, the theoretical model predicts mirrored responses of regional imports and exports depending on the hit/non-hit classification, which is broadly consistent with those observed in the empirical model

The theoretical model allows us to perform a counterfactual analysis that excludes the fall in energy supply. To do this, we now set $\varepsilon_{e^*,t} = 0$ implying that there is no reduction in energy supply in the subsequent periods. The blue dashed lines in Figure 5 show the counterfactual responses from this specification. As expected, the subsequent reduction in energy supply creates a stronger and more prolonged decline in local output and trade, particularly in the hit regions. This is a direct consequence of a lower permanent income induced by a persistently lower energy supply.

As Figure 6 indicates, the higher the persistence of the energy supply shock is, the stronger the fall of output on impact in hit regions. An expected prolonged lower energy supply in the future periods results in a lower consumption and output in the current periods. Inflation becomes slightly lower without an energy fall, reflecting the lower marginal cost with lower energy prices. On the other hand, in the absence of a persistent electricity fall, non-hit regions would have experienced a somewhat higher level of output as well as exports and imports following an output shock in other regions. However, judging from the modest gap between the two lines, the effect is rather weak indicating that the major impact is driven by the fall in nationwide output. The upshot is that while a persistent fall in energy supply induces a significant negative impact for hit regions, it creates a relatively limited negative impact for non-hit regions.

# 6 Empirical counterfactual analysis of 'no follow-up energy supply cut'.

The results from the theoretical model suggest that the persistent fall in electricity supply confounded the impact on both hit and non-hit regions, although the negative impact on macroeconomic variables are more emphasised in hit regions. We examine this closer by

Figure 5: IRFs of a decrease in regional productivity and output in other regions
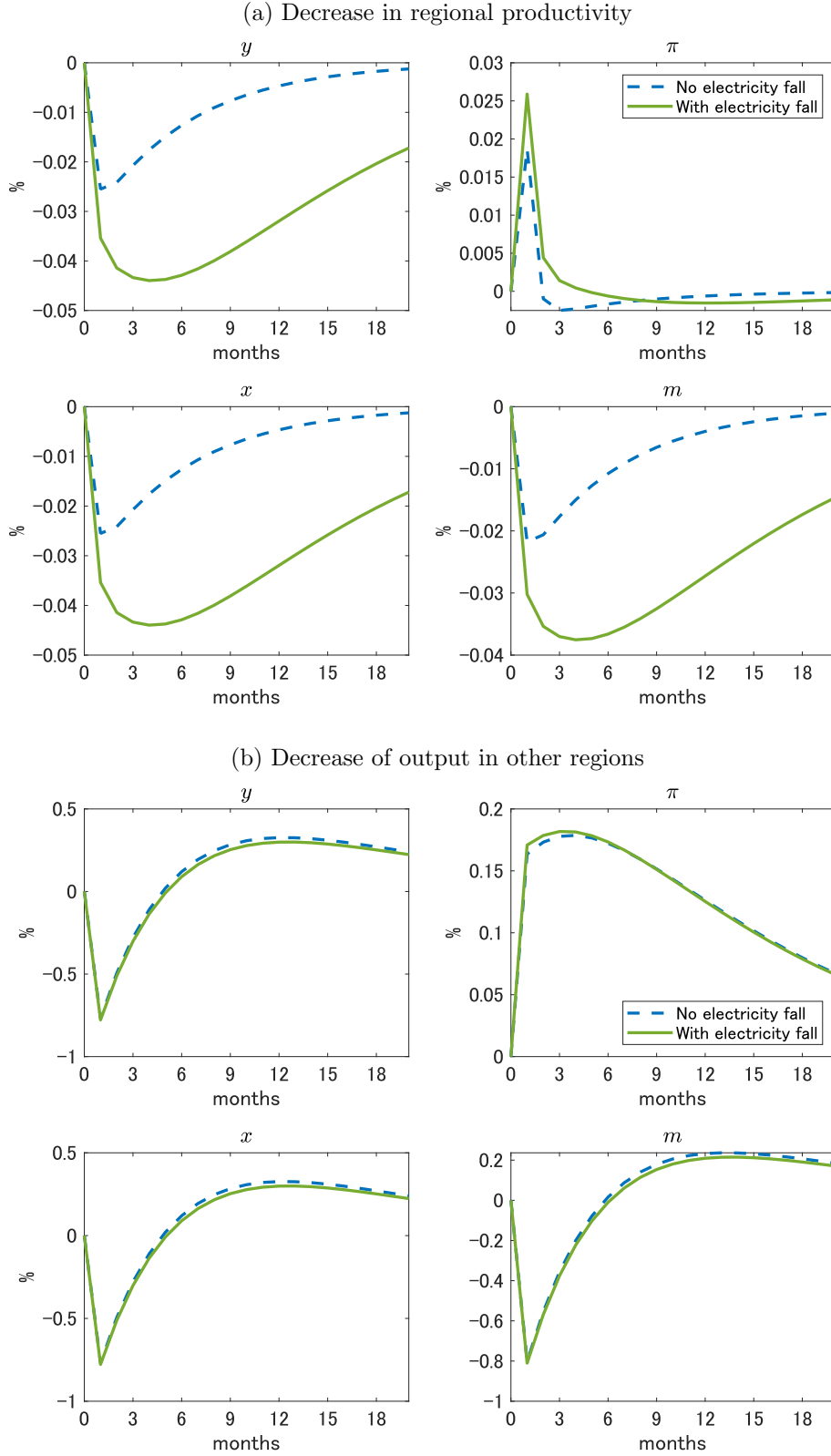
(a) Decrease in regional productivity

(b) Decrease of output in other regions

Impulse responses from a shock in (a) regional productivity, $\varepsilon_{a,t}$ and energy supply $\varepsilon_{e^*,t}$, which can be used to approximate one hit region; (b) output in other regions, $\varepsilon_{y^*,t}$ and energy supply $\varepsilon_{e^*,t}$, which can be used to approximate for non-hit regions. The green solid line presents the benchmark case where (a) the regional shock and energy supply shock take simultaneously; (b) the shock on output in other regions and energy supply shock take simultaneously. The blue dashed line represents the same productivity shock with zero persistence of energy supply shock.

22

Figure 6: Persistence of energy supply shock and fall in output
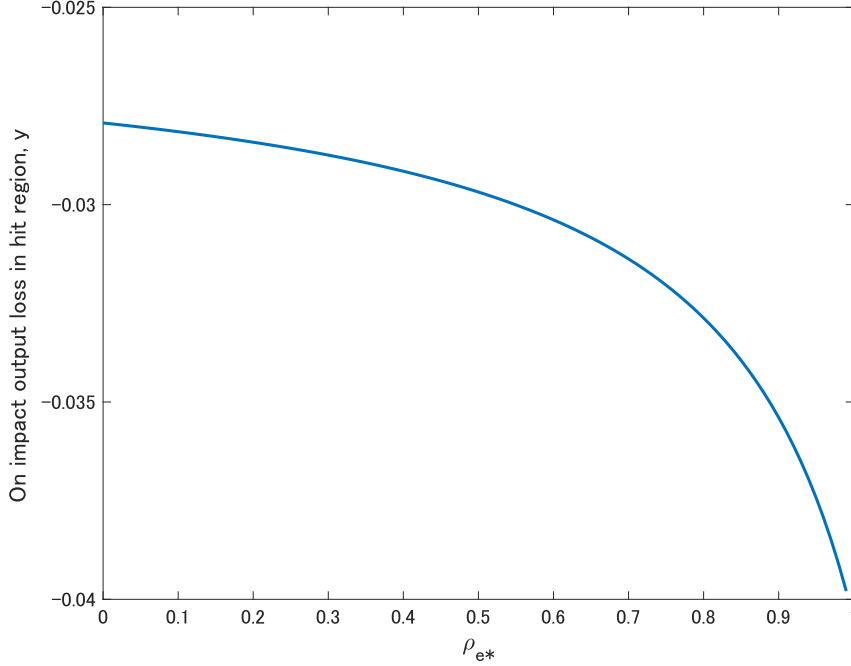
The line presents the fall in production on impact in hit region, y_1, with respect to different persistence of energy supply shock, ρ_{e^*}.

using our empirical model to construct a counterfactual policy scenario.

Following the theoretical model, we introduce energy supply and regional interdependence to our BPVAR. These two features will allow us to generate counterfactual scenarios based on an alternative hypothetical energy supply path. Similar approaches that deal with dynamic interdependencies (in non-disaster contexts) have been adopted by Canova and Ciccarelli (2004, 2009) and Dées and Güntner (2017). The model is described in detail in the Appendix A.2. We use our extended BPVAR to perform counterfactual policy analysis based on conditional in-sample forecasts. Within our context, conditional forecasts can be thought of as scenarios that involve projections of a set of variables of interest on future paths of some other variables, in our case this is total electricity supply.[25]

We augment the vector of endogenous variables with one additional variable, the total electricity supply for each of the included regions. To limit the number of parameters to estimate, we limit our analysis to the regions of Chubu, Kanto, Kinki and Tohoku. Hokkaido and Hokuriku are omitted since these were less affected by the earthquake and tsunami in 2011, as evidenced in section 4.1. Our sample period now runs from April 2008

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[25]Conditional forecasts for scenario analysis have been used for stress tests conducted in the US, Euro area and the UK in the aftermath of the 2007 financial crisis, or another example, for informing monetary policy decisions conditional on specific paths of the policy rate. Recent studies that use conditional forecasts are, Bryan and Morten (2019), Stock and Watson (2002), and Giannone et al. (2010, 2012, 2014). Details on the approach that we follow to calculate conditional forecasts can be found in Waggoner and Zha (1999).

Figure 7: Counterfactual paths-electricity supply
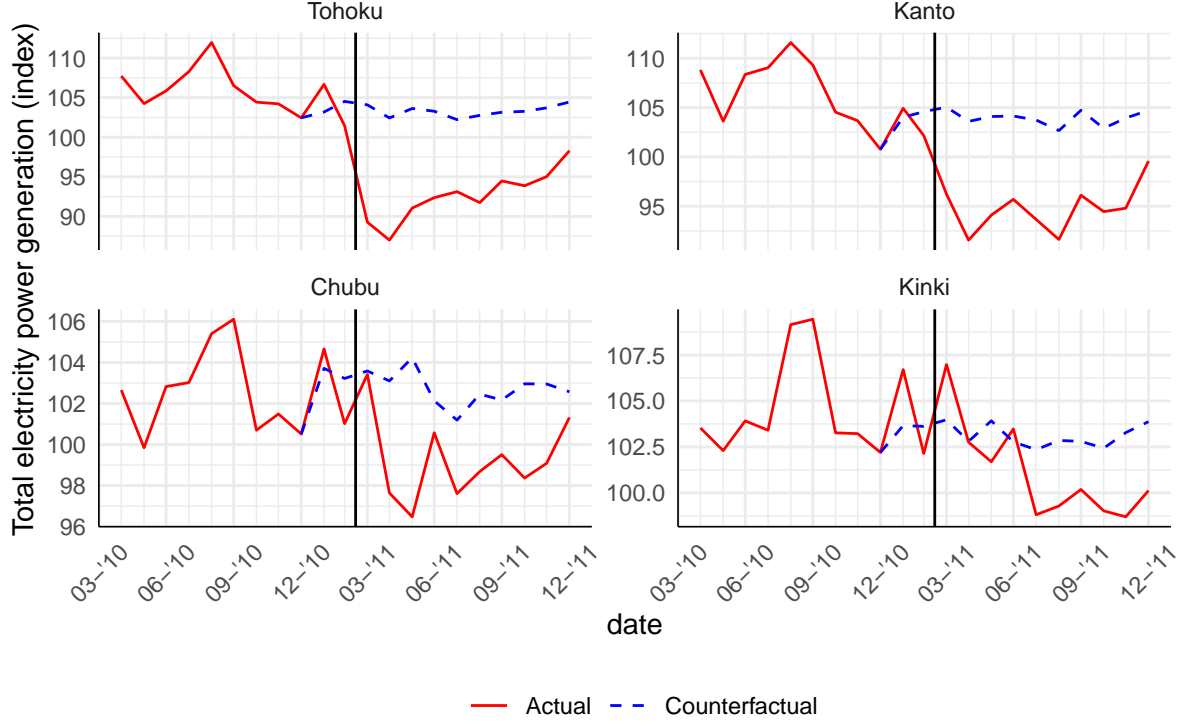
The counterfactual paths used for the conditional forecasts, return and follow a pre-March 2011 trend. Data points and labels are set at the last day of the month.

up to December 2011 and we perform conditional forecasts from May 2011, that is, the first month after the earthquake, until December 2011. As Figure 7 shows, we conduct conditional forecasts based on the assumption that total electricity supply follows a higher path that corresponds to levels prior to the 2011 earthquake.[26] As a result, macroeconomic variables in the current period depend on all expected future passes of counterfactual electricity supply. Practically, this aims to approach the dynamics of a counterfactual world in which the government did not order the closure of the nuclear plants across the country.

The results for the counterfactuals are depicted in Figure 8. The regions are ordered from top to bottom, from most exposed to the earthquake (Tohoku and Kanto) to the least (Chubu and Kinki). As before, the focus is on industrial production, prices and exports. Each plot indicates the past data, with the continuation of the forecast period (in green solid). Then we present two (in-sample) forecasts. The red dash-dot line presents the median forecast conditional on the actual process of electricity supply. The blue dashed line presents the median forecast conditional on the counterfactual electricity supply series

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[26]In particular, the paths of electricity supply are generated by estimating the same model as described above and obtaining the unconditional forecasts of electricity supply, from January 2011 up to December 2011. Note that in our context, unconditional forecasts simply implies that no knowledge is assumed for the future path of the variables.

as described above.

The following messages emerge from the results. Firstly, and most importantly for this study, the counterfactual forecasts of IP, exports and prices are consistently above the forecasts based on the actual path of electricity. The results suggest that the empirical model is in line with the predictions from the theoretical model, pointing that the Japanese regional economies did experience a loss in production and trade due to the persistent electricity shutdown. Second, the magnitude of the effect (i.e. the gap between the blue-dashed and red dotted lines) for both IP and exports is much larger for the hit regions (Tohoku and, to a lesser extent, Kanto) than the non-hit ones, corroborating the evidence from the theoretical model. We also notice that the median counterfactual for Tohoku exports overshoots the actual data, suggesting that exports would completely return to pre-disaster levels in the absence of a shortage of electricity supply. Compared with the forecast of Tohoku IP, the forecast for exports appears a bit too optimistic in our view. Since the tsunami had a large destructive impact on the ports of Tohoku, the recovery exports lagged for a longer period than production (Hamano and Vermeulen, 2020).
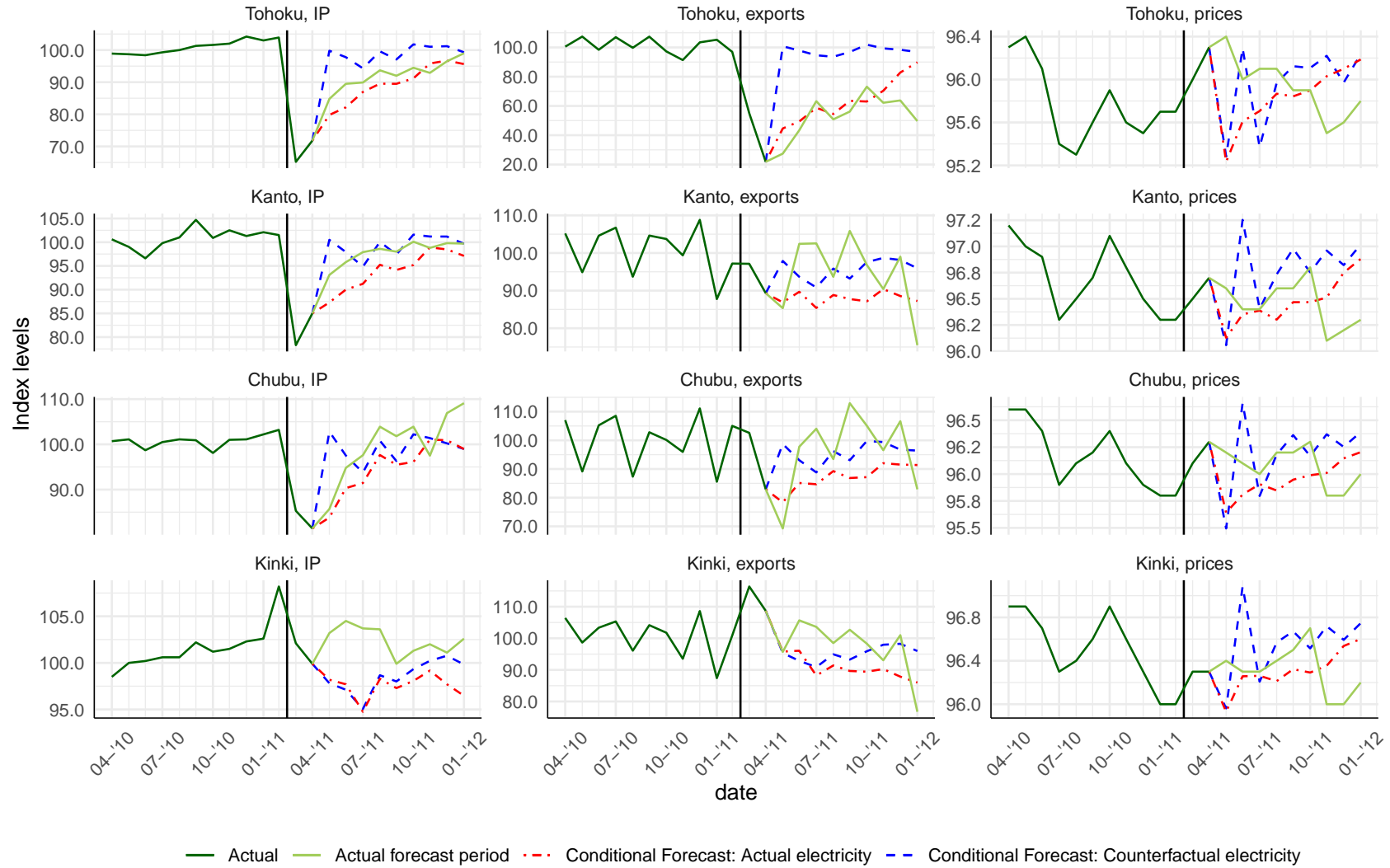
Another result that is revealed by the BPVAR is that Kinki presents a divergence between the two forecasts, in contrast to the other three regions that exhibit a convergence of their IP and exports forecasts. The divergence in Kinki is consistent with the idea the persistent electricity process became increasingly important for this region's economic performance in the aftermath of the earthquake. Next, note that in most cases, the median estimates of the conditional forecasts based on the observed electricity supply (red dotted line) track rather well the trends in the observed data (the green solid line), capturing, for example, the general increase in IP observed in three out of four cases, the rise in exports in two regions, and the fall of exports in one. However, admittedly, the timing could have been better. Similarly, for prices, the median forecasts capture well the actual path of regional CPIs. Note that at the end of the forecasting period, the median inflation forecasts for all regions appear to move upwards, diverging from the actual data.

In Appendix C.1, we present the same two conditional forecasts together with their confidence bands. Although the results cannot be said to statistically differ from the observed data, we take confidence in the consistent patterns across regions and over time, the consistency with the theoretical model, and particularly, the notable differences between the forecasts based on the actual and the counterfactual electricity supply paths. These clearly suggest that the regions experienced a loss in production and trade due to the shutdown of the nuclear power plants.

7 Conclusion

Shocks from natural disasters will strike local economies, which are often integrated with a larger national economy. This paper uses the case of the 2011 Great East Japan Earth-

Figure 8: Scenario analysis - Forecasts based on counterfactual electricity supply

Legend: —— Actual —— Actual forecast period ·–·– Conditional Forecast: Actual electricity – – Conditional Forecast: Counterfactual electricity

Observed and conditional forecasts from a BPVAR model on four regions (Tohoku, Kanto, Chubu and Kinki) and five variables (IP, exports, prices, imports (not shown but available upon request). The model allows for interactions across the regions. The vertical black line indicates the date of the first main earthquake and tsunami. The first period of forecast is May 2011. The solid dark green line present the pre-forecast data. The solid light green line presents the actual realisation of the data during the forecast period.

quake to study regional spill-overs of follow-up disasters. We separate two major exogenous processes that represent the event, notably an immediate production shock in one set of regions, followed by a persistent nation-wide reduction in nuclear electricity supply. We estimate a Bayesian Panel VAR model to demonstrate regional heterogeneity in the macroeconomic indicators. We also develop a DSGE model that rationalises these results through a mechanism of regional spillovers. Finally, we provide simulations of a case where the national electricity reduction did not occur, representing a hypothetical case where the Fukushima nuclear power plant was not affected by the tsunami.

For the economic indicators, we focus on industrial production, prices, and trade variables. Each of these are observed monthly for each region in Japan. We estimate impulse response functions and find that price pressures are nationally propagated but short-lived. In contrast, trade indicators for the hit regions point towards a significant loss in trade while the responses of some non-hit areas, suggest that goods exports and imports are replaced to non-hit areas. Industrial production is negatively affected nationally. The impact is stronger and more persistent in the hit regions.

Next, we seek to disentangle the shock of the natural disaster from the persistent energy shock that was triggered by the accident at the Fukushima nuclear power plant. We do so by extending the DSGE model of a small open economy of Galí and Monacelli (2005). We find that the persistent shortage of electricity supply aggravated the national economic production shock attributable to the natural disaster by delaying and slowing down the recovery of the disaster hit areas. The counterfactual results from the empirical model, in line with the predictions from the theoretical one, suggest that the Japanese regional economies did experience a loss in production and trade due to the electricity shutdown that persisted for a long time.

From a policy perspective, our study highlights the key role of the government and institutions in times of such extreme events. The government and institutions may devise regional recovery plans that help anchor expectations and contribute to stability, so that they can strengthen the ability of the regional economies, and thus that of the whole country, to absorb shocks from natural disasters. When this is the case, our paper shows that better outcomes can be observed for real economic indicators, prices and trade.

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A Appendix.

A.1 Bayesian Panel VARX

In this paper, we use a Bayesian Panel VARX model to identify the impact of earthquake events using the excessive Tohoku IP shock as an exogenous variable, henceforth 'earthquake shock'.The general form of the Panel VARX model for region i at time t with $i = 1, ..., N$ is given by:

$$y_{i,t} = A_i^1 y_{i,t-1} + ... + A_i^p y_{i,t-p} + C_{i,t} x_t + \varepsilon_{i,t}, \tag{A-1}$$

where $y_{i,t}$ denotes a $n \times 1$vector of n endogenous variables of region i at time t for p, where $p = 4$ in our case. $A_{i,t}^p$ is a $n \times n$ matrix of coefficients, while x_t is the $m \times 1$ vector of exogenous variables and $C_{i,t}$ is the $n \times m$ matrix connecting the endogenous to the exogenous variables. Last, $\varepsilon_{i,t}$ denotes a $n \times 1$ vector of residuals with $\varepsilon_{i,t} \sim N(0, \Sigma)$, where Σ is a diagonal matrix with Σ_i elements in the diagonal. Note that, as the focus of this first part of the empirical analysis is the impact of common exogenous earthquake shocks rather than spillovers across regions, cross-region inter-dependencies assumed to be zero, that is, the A_i^p matrix in (A-1) is block diagonal.

By transposing (A-1), writing in compact form and stacking over T sample periods, we get

$$Y_i = X_i B_i + e_i, \tag{A-2}$$

where

$$Y_i = \begin{pmatrix} y'_{i,1} \\ y'_{i,2} \\ \vdots \\ y'_{i,T} \end{pmatrix}_{T \times n} , X_i = \begin{pmatrix} y'_{i,0} & \cdots & y'_{i,1-p} & x'_0 \\ y'_{i,1} & \cdots & y'_{i,2-p} & x'_1 \\ \vdots & \ddots & \vdots & \vdots \\ y'_{i,T-1} & \cdots & y'_{i,T-p} & x'_T \end{pmatrix}_{T \times k} ,$$

$$B_i = \begin{pmatrix} (A_i^1)' \\ \vdots \\ (A_i^p)' \\ C_i' \end{pmatrix}_{k \times n} , e_i = \begin{pmatrix} \varepsilon'_{i,1} \\ \varepsilon'_{i,2} \\ \vdots \\ \varepsilon'_{i,T} \end{pmatrix}_{T \times n} ,$$

with $k = np + m$. Equation (A-2) reformulates in vectorised form as

$$y_i = \bar{X}_i \beta_i + \varepsilon_i, \tag{A-3}$$

where $y_i = vec(Y_i)$, $\bar{X}_i = (I_n \otimes X_i)$, $\beta_i = vec(B_i)$ and $\varepsilon_i = vec(e_i)$. Note that $\varepsilon_i \sim N(0, \Sigma)$ as defined earlier, now takes the following form $\varepsilon_i \sim N(0, \bar{\Sigma}_i)$, with $\bar{\Sigma}_i = \Sigma_i \otimes I_T$. Next, in order to examine how each region responds to earthquake shocks, we introduce

cross-sectional heterogeneity; essentially allowing our model to obtain a domestic VAR for each region. We introduce this property by assuming that for each region i, β_i can be expressed as

$$\beta_i = b + b_i, \tag{A-4}$$

with b a $k \times 1$ vector of parameters and $b_i \sim N(0, \Sigma_b)$. Therefore, it follows that the distribution of β_i will be

$$\beta_i \sim N(b, \Sigma_b), \tag{A-5}$$

which implies that the Panel VAR coefficients will differ across regions, but they are drawn from a normal distribution with shared mean and variance. In order to derive the posterior distribution of β_i we follow the hierarchical prior approach developed by Jarocinski (2010). The reason is that the identification methodology adopted under this strategy, assumes that $\{\beta_i, \Sigma_i\}$, and $\{b, \Sigma_b\}$ are unknown, random variables, and therefore, they are all including in the estimation process, which implies that they are endogenously estimated by the model. This makes this strategy much richer and sophisticated compared with other techniques which only treat β_i as unknown (see for example Zellner and Hong, 1989).

The complete posterior distribution for the model is given by

$$\pi(\beta, b, \Sigma_b, \Sigma \mid y) \propto \pi(y \mid \beta, \Sigma)\pi(\beta \mid b, \Sigma_b)\pi(b)\pi(\Sigma_b)\pi(\Sigma). \tag{A-6}$$

That is, the full posterior distribution is equal to the product of the data likelihood function $\pi(y \mid \beta, \Sigma)$, along with the conditional prior distributions $\pi(\beta \mid b, \Sigma_b)$ for β and the priors of $\pi(b)$, $\pi(\Sigma_b)$ and $\pi(\Sigma)$ for b, Σ_b and Σ respectively. In particular, the likelihood function is given by

$$\pi(y \mid \beta, \Sigma) \propto \prod_{i=1}^{N} \left| \bar{\Sigma}_i \right|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(y_i - \bar{X}_i\beta_i)'(\bar{\Sigma}_i)^{-1}(y_i - \bar{X}_i\beta_i) \right), \tag{A-7}$$

while the prior distributions of all parameters are set as follows. Start with β_i, given (A-4) and (A-5), the prior density for the vector of coefficients β_i is

$$\pi(\beta \mid b, \Sigma_b) \propto \prod_{i=1}^{N} |\Sigma_b|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(\beta_i - b)'(\Sigma_b)^{-1}(\beta_i - b) \right). \tag{A-8}$$

Next, the prior distribution for Σ_i is a diffuse prior given by

$$\pi(\Sigma) \propto \prod_{i=1}^{N} |\Sigma_i|^{-(n+1)/2}, \tag{A-9}$$

while, similarly for the hyper-parameter b, the prior assumed is diffused

$$\pi(b) \propto 1. \tag{A-10}$$

Last, for the hyper-parameter Σ_b, the prior chosen, follows the design of the Minnesota prior. Specifically, the full covariance matrix is given by

$$\Sigma_b = (\lambda_1 \otimes I_q)\Omega_b, \tag{A-11}$$

where Ω_b, is a diagonal matrix which is constructed based on three different assumptions (Litterman, 1986).[27] The further the lag, the more confident one should be that coefficients linked to this lag will have a zero value, implying that the variance should be smaller on distant lags. Also, similarly, one should be more certain that the variance of the coefficients relating variables to past values of other variables is small. Finally, it is assumed that little is known about exogenous variables. Regarding, λ_1, this represents the overall tightness parameters. When $\lambda_1 = 0$, all β_i's will take the same value, b (pooled estimator). As λ_1 is becoming larger, the β_i's are allowed to vary across regions, while as $\lambda_1 \to \infty$, the prior becomes uninformative. As the results might be sensitive to the use of this prior (Jarocinski, 2010), particularly when the number of regions included in our analysis is bigger than five, we use the following uninformative prior

$$\pi(\lambda_1) \propto \lambda_1^{-\frac{1}{2}}, \tag{A-12}$$

where $\lambda_1 = 0.01$, following typical analysis in the literature.

Having all priors in hand and substituting into (A-6), one is able to obtain the full posterior distribution. The conditional conjugacy of the priors implies that all conditional posteriors are also normal, inverted gamma or inverted Wishart, which enables us to use a Gibbs sampling algorithm to approximate the posterior distributions of each of the model parameters (see further detailed below).

A.1.1 Identification

To identify the Panel VARX model correctly and allow for meaningful interpretation of the impulse responses, we adopt the following strategies. First, as already mentioned, we identify the impact of earthquake events as an exogenous variable. This strategy implies that the earthquake shock affects all the macroeconomic variables in the system and across regions, contemporaneously, but none of them is allowed to affect the earthquake variable. Secondly, the block of endogenous, regional variables is identified through Cholesky decomposition that consists of obtaining an upper triangular matrix A_0 such that $A_0 A_0' = \Sigma$, where A_0 represents the contemporaneous impact of the structural shocks $v_{i,t}$ such that $\varepsilon_{i,t} = A_0 v_{i,t}$.

The ordering of the variables that we use in this paper is standard in the literature (Eichenbaum and Evans, 1995; Christiano et al., 1999) and it is as follows: IP is ordered first, followed by CPI inflation and last, the trade variables (imports/exports). The identification strategy implies that a shock to the regional IP has a contemporaneous effect on all other domestic variables in the region but none of them can affect the regional IP (except, of course, the exogenous earthquake shock). Similarly, a shock to the regional CPI inflation impacts all the other variables within the region apart from IP but a shock

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[27]For a detailed explanation of the Minnesota prior and the construction of Ω_b, see Blake and Mumtaz (2012).

in IP is the only regional shock that could affect prices (except of the common exogenous earthquake shock).

Next, producing impulse responses with the Panel VARX model is straightforward as the model can ultimately results in the estimation of a set of N independent VAR models, one for each region. Moreover, the Bayesian framework that we adopt makes it possible to integrate the impulse responses calculation into the Gibbs sampling framework that is set out below. In particular, to calculate the impulse responses functions, we obtain the predictive distribution $f(y_{t+1:t+h} \mid y_t)$ where h is the forecasting period. The logic is that at each iteration of the estimation algorithm (see below), given the draw of β from its posterior distribution we obtain $A_i^1, ..., A_i^p$ and given the draw of Σ from its conditional distribution, we obtain A_0 by computing the Cholesky factor of Σ. Having these in hands, we generate recursively the simulated values $\widetilde{y}_{T+1}, \widetilde{y}_{T+2}, \ldots, \widetilde{y}_{T+h}$ from (A-1) by replacing $\varepsilon_t = A_0 \upsilon_t$.

A.1.2 Posterior distributions

We start with the posterior of β_i. Starting from the full posterior distribution in (A-6) and relegating any term not involving β_i to the proportionality constant, yields

$$\pi(\beta_i|\beta_{-i}, y, b, \Sigma_b, \Sigma) \propto \pi(y \mid \beta, \Sigma)\pi(\beta \mid b, \Sigma_b), \tag{A-13}$$

where β_{-i} denotes all β coefficients except for β_i. Now, inserting the likelihood function (A-7) and the prior density of β_i (A-8), into the above equation indicates that the posterior for β_i is multivariate normal,

$$\pi(\beta_i \mid \beta_{-i}, y, b, \Sigma_b, \Sigma) \sim \mathcal{N}(\ddot{\beta}_i, \ddot{\Omega}_i), \tag{A-14}$$

where $\ddot{\Omega}_i = [\Sigma_i^{-1} \otimes X_i'X_i + \Sigma_b^{-1}]^{-1}$, $\ddot{\beta}_i = \ddot{\Omega}_i[(\Sigma_i^{-1} \otimes X_i')y_i + \Sigma_b^{-1}b]$. Next, for the posterior distribution of b, starting again from (A-6) and relegating to the normalising constant any term not involving b to the proportionality constant yields: $\pi(b \mid y, \beta, \Sigma_b, \Sigma) \propto \pi(\beta \mid b, \Sigma_b)\pi(b)$. Following the same logic as before, we insert (A-8) and (A-10) in the above equation, and rearranging, to show that the posterior of b is a multivariate normal distribution

$$\pi(b \mid y, \beta, \Sigma_b, \Sigma) \sim \mathcal{N}(\beta_\vartheta, N^{-1}\Sigma_b), \tag{A-15}$$

where $\beta_\vartheta = N^{-1} \sum_{i=1}^{N} \beta_i$ is the arithmetic mean over the β_i. Following exactly the same process we can show that the posterior distribution for Σ_b is an inverse Gamma distribution

$$\pi(\Sigma_b \mid y, \beta, b, \Sigma) \sim IG\left(\frac{\ddot{s}}{2}, \frac{\ddot{u}}{2}\right), \tag{A-16}$$

where $\ddot{s} = s_0$ that is set equal to a very small number $s_0 < 0.001$ and $\ddot{u} = u_0 + \sum_{i=1}^{N}\left\{(\beta_i - b)'\Omega_b^{-1}(\beta_i - b)\right\}$. Finally, once again relegating to the proportionality constant any term not involving Σ_i, one can obtain the conditional distribution of Σ_i that is an inverse Wishart distribution

$$\pi(\Sigma_i \mid \Sigma_{-1}, y, \beta, b) \sim IG\left(\ddot{S}_i, T\right), \tag{A-17}$$

where T denotes the degrees of freedom and $\ddot{S}_i = (Y_i - X_i B_i)'(Y_i - X_i B_i)$.

A.1.3   Estimation algorithm

Having all these elements in hand, we apply the following Gibbs algorithm to derive the model parameters. We first define starting values for β, Σ, b, and Σ_b. For $\beta^{(0)}$ we use OLS estimates for $\hat{\beta}_i$; similarly we set starting values for $\Sigma^{(0)}$ by using OLS estimates of $\hat{\Sigma}_i$. For b we set $\beta_{\vartheta}^{(0)} = N^{-1}\sum_{i=1}^{N}\hat{\beta}_i$, while for Σ_b we set $\lambda_1^{(0)} = 0.01$, which from (A-12) give us $\sqrt{\lambda_1^{(0)}} = 0.1$. Note that, in our experience, the choice of starting values has negligible impact on the final results because the number of the iterations of the algorithm is large enough. The Gibbs sampler consists of the following steps: at each iteration [28]:

1. draw b from (A-15);

2. given an estimate of b, draw Σ_b from (A-16);

3. given estimates of b and Σ_b from previous steps, draw β from (A-14);

4. given estimates of b, Σ_b and β from previous steps, draw Σ from (A-17).

A.2   Panel VARX with cross-sectional spillovers

To see the procedure, rewrite (A-2) in a simultaneous equations format as
$$y_t' = X_t B + \varepsilon_t, \tag{A-18}$$

where now $X_t = (y_{t-1}' \ldots y_{t-p}' \ x_t')_{1 \times k}$ and $B = \begin{pmatrix} (A^1)' \\ \vdots \\ (A^1)' \\ C' \end{pmatrix}_{k \times Nn}$

This equation reformulates into a vectorised form as
$$y_t = \bar{X}_t \beta + \varepsilon_t', \tag{A-19}$$

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[28]Note that we use 50,000 total iterations discarding the first 45,000 as burn-in. As pointed out by Dieppe et al., 2016, this number of total and burn in iterations is sufficient to ensure convergence of the Gibbs algorithm and lead to accurate posterior distributions.

where $\bar{X}_t = (I_{Nn} \otimes X_t)$ $\beta = vec(B)$. Allowing for inter-dependencies means that both the variance-covariance matrix Σ and the coefficient matrix A^p do not need to be block diagonal anymore. Particularly for the matrix Σ, we allow a higher degree of flexibility by assuming that the error term follows the normal distribution as

$$\varepsilon_{\iota,t} \sim N(0, \Sigma) \quad \Sigma = \varphi \ddot{\Sigma}, \tag{A-20}$$

where φ is a scaling random variable following an inverse Gamma distribution as,

$$\varphi \sim IG\left(\frac{\alpha_0}{2}, \frac{\omega_0}{2}\right). \tag{A-21}$$

Now, the problem that arises related to the curse of dimensionality, as the total number of parameters to be estimated in the model ($h = N^2n^2p$) easily exceeds the available sample period. To deal with this issue, we follow Canova and Ciccarelli (2013), by assuming that the h elements of the vector of coefficients β, can be expressed as a linear function of a significantly lower number of structural factors r,

$$\beta = \sum_{i=1}^{r} \Xi_i \vartheta_i, \tag{A-22}$$

where ϑ_i are vectors of dimension d_i and contain the structural factors, while Ξ_i are selection matrices of dimension $h \times d_i$ that take values of either 0 or 1 picking the relevant elements of ϑ_i. To identify the model we follow the authors by assuming $r = 5$ structural factors. In particular, ϑ_1 captures components which are common across regions and variables, say its dimension is $d_1 = \tau$; ϑ_2 captures components which are common within regions, thus its dimension equals the number of regions $d_2 = N$; ϑ_3 captures components which are variable specific, thus its dimension equals the number of variables $d_3 = n$; ϑ_4 captures lag specific components and comprises $d_4 = p - 1$ coefficients and last, ϑ_5 captures the effects of the exogenous variables in the model and contains $d_5 = m$ coefficients. Factoring β as in (A-22) allow us to reduce the number of coefficients to estimate from h elements to $d = \tau + N + n + (p - 1) + m$. Practically, using (A-22) in (A-19), we obtain

$$y_i = \mathfrak{J}_i \times \vartheta + \varepsilon_i, \tag{A-23}$$

where $\mathfrak{J}_i = \bar{X}_i \times \Xi$. Intuitively, the decomposition presented in (A-23) allows us to measure the relative importance of common, unit specific and variable specific influences in fluctuations in y. As Canova and Ciccarelli (2013) point out, the slow moving structure of $\mathfrak{J}_i$ implies that $\bar{X}_i$ capture low frequency movements present in the Panel VARX. This feature is particularly important in medium term out-of-sample forecasting exercises that we conduct in this paper. It is possible to stack (A-23) over T and estimate the model by OLS methods. However, we will adopt the Bayesian avenue as when the sample size

is short, as it is the case in this paper, we need to practically select priors that could help to obtain economically meaningful estimates, something that it is hard to obtain with classical techniques.

Our objective now is to estimate the three parameters ϑ, $\ddot{\Sigma}$ and φ. Once estimate ϑ, it will be possible to recover draws for β from (A-22). As in Appendix A.1, by using Bayes' rule, the complete posterior distribution for the model is given by

$$\pi(\vartheta, \ddot{\Sigma}, \varphi \mid y) \propto f(y \mid \vartheta, \ddot{\Sigma}, \varphi)\pi(\vartheta)\pi(\ddot{\Sigma})\pi(\varphi). \tag{A-24}$$

That is, the posterior distribution equals to the product of the data likelihood function with the respective prior distributions of ϑ, $\ddot{\Sigma}$ and φ. Starting with the likelihood function, it is given by

$$f(y \mid \vartheta, \ddot{\Sigma}, \varphi) \propto (\varphi)^{-TNn/2} \left|\ddot{\Sigma}\right|^{-\frac{T}{2}} \prod_{i=1}^{T} exp\left(-\frac{1}{2}\varphi^{-1}(y_t - \mathfrak{J}_t\vartheta)'(\ddot{\Sigma})^{-1}(y_t - \mathfrak{J}_t\vartheta)\right). \tag{A-25}$$

Next with the priors, the prior for ϑ is multivariate normal given by

$$\pi(\vartheta \mid \vartheta_0, \Theta_0) \propto \exp\left[-\frac{1}{2}(\vartheta - \vartheta_0)'\Theta_0^{-1}(\vartheta - \vartheta_0)\right], \tag{A-26}$$

where the mean ϑ_0 is set as a vector of zeros and the form of covariance Θ_0 is simply an uninformative prior and is therefore set as a diagonal matrix with large values. For $\ddot{\Sigma}$, an uninformative prior is used as follows

$$\pi(\ddot{\Sigma}) \propto \left|\ddot{\Sigma}\right|^{-(Nn+1)/2}, \tag{A-27}$$

while for φ, as we mentioned above, an inverse Gamma distribution is used with shape $\frac{\alpha_0}{2}$ and scale $\frac{\omega_0}{2}$ as

$$\pi(\varphi) \propto \varphi^{-\frac{\alpha_0}{2}-1} \exp\left(\frac{-\omega_0}{2\varphi}\right). \tag{A-28}$$

Similar to Appendix A.1, combining the likelihood function in (A-25) with the priors in equations (A-26), (A-27), (A-28) and substituting into (A-24), one is able to obtain the full posterior distribution. As it is not possible to use analytical methods to integrate out the posterior distributions we will use a Gibbs sampling algorithm to approximate them. Details on the posterior distributions of the model parameters and the Gibbs algorithm can be found above.

The Panel VARX with dynamic interrelationships is used to produce forecasts as described in Section 6. Similar to the derivation of impulse responses, producing forecasts is a simple task given that the Panel VARX can be seen as a set of N independent VAR models to

be estimated.

As we are interested in performing conditional forecasts for scenario analysis, we follow the methodology of Waggoner and Zha (1999) for constructing the posterior predictive distribution of the conditional forecasts. We can then integrate this into the Gibbs sampler framework described next in order to produce the posterior distribution of conditional forecasts (see Dieppe et al., 2016 for more details on the description of the algorithm that we adopt).

A.2.1 Estimation of the Panel VARX with interrelationships

Combining (A-25) to (A-28) one can obtain the joint posterior as

$$f(y \mid \vartheta, \ddot{\Sigma}, \varphi) \propto \prod_{i=1}^{T} \left\{ \exp\left(-\frac{1}{2} \varphi^{-1} (y_t - \mathfrak{J}_t \vartheta)' (\ddot{\Sigma})^{-1} (y_t - \mathfrak{J}_t \vartheta) \right) \right\} \times$$
$$\exp\left(\frac{-\omega_0}{2\varphi} \right) \times \varphi^{-(NnT + \alpha_0)/2 - 1} \times \left| \ddot{\Sigma} \right|^{-(T + Nn + 1)/2} \times$$
$$\exp\left[-\frac{1}{2} (\vartheta - \vartheta_0)' \Theta_0^{-1} (\vartheta - \vartheta_0) \right]. \tag{A-29}$$

Next, in order to obtain the conditional posterior distributions for ϑ, $\ddot{\Sigma}$ and φ, we start from (A-29) and relegate any term not involving ϑ to the proportionality constant in order to obtain the conditional posterior of ϑ and then rearranging we have, $\pi(\vartheta \mid y, \ddot{\Sigma}, \varphi) \propto \exp\left[-\frac{1}{2}(\vartheta - \vartheta_\Upsilon)' \Theta_\Upsilon^{-1} (\vartheta - \vartheta_\Upsilon) \right]$, where $\Theta_\Upsilon = (\mathfrak{J}_t I_\Sigma \mathfrak{J}_t' + \Theta_0^{-1})^{-1}$ and $\vartheta_\Upsilon = \Theta_\Upsilon (\mathfrak{J}_t I_\Sigma y + \Theta_0^{-1} \vartheta_0)$. This is the kernel of a multivariate normal distribution,

$$\pi(\vartheta \mid y, \ddot{\Sigma}, \varphi) \sim \mathcal{N}(\vartheta_\Upsilon, \Theta_\Upsilon). \tag{A-30}$$

Next, relegating to the proportionality constant any term not involving $\ddot{\Sigma}$ in (A-29) and rearranging we obtain, $\pi(\ddot{\Sigma} \mid y, \vartheta, \varphi) \propto \left| \ddot{\Sigma} \right|^{-(T + Nn + 1)/2} \times \exp\left(-\frac{1}{2} tr\left\{ \ddot{\Sigma}^{-1} \bar{\Psi} \right\} \right)$ where $\bar{\Psi} = \varphi^{-1} (y - \mathfrak{J} I_\vartheta)(y - \mathfrak{J} I_\vartheta)'$. This is the kernel of an inverse Wishart distribution with scale $\bar{\Psi}$ and T degrees of freedom,

$$\pi(\ddot{\Sigma} \mid y, \vartheta, \varphi) \propto \sim \mathcal{IW}(\bar{\Psi}, T). \tag{A-31}$$

Last, relegating to the proportionality constant any term not involving $\ddot{\phi}$ in (A-25) and rearranging we get : $\pi(\varphi \mid y, \vartheta, \ddot{\Sigma}) \sim \varphi^{-\frac{\ddot{\alpha}}{2} - 1} \exp\left(\frac{-\ddot{\omega}}{2\varphi} \right)$, where $\ddot{\alpha} = NnT + \alpha_0$ and $\ddot{\omega} = \left[tr\left((y - \mathfrak{J} I_\vartheta)(y - \mathfrak{J} I_\vartheta)' \ddot{\Sigma}^{-1} \right) + \omega_0 \right]$. This is the kernel of an inverse Gamma distribution

$$\pi(\varphi \mid y, \vartheta, \ddot{\Sigma}) \propto \sim IG\left(\frac{\ddot{\alpha}}{2}, \frac{\ddot{\omega}}{2} \right). \tag{A-32}$$

Having obtained all posteriors, we can eventually apply the following Gibbs algorithm to derive the model parameters. We first have to define starting values for ϑ, $\ddot{\Sigma}$ and φ. For $\vartheta^{(0)}$ we use OLS estimates for $\hat{\vartheta}$; for $\Sigma^{(0)}$, we use (A-23) to obtain $\hat{\ddot{\Sigma}}$ while for $\varphi^{(0)}$ the value is set to 1. Then, the Gibbs sampling proceeds through the following steps: at each iteration

1. draw $\ddot{\Sigma}$ from (A-31);

2. draw φ from (A-32);

3. given estimates of φ and $\ddot{\Sigma}$, use (A-20) to compute $\Sigma = \varphi \ddot{\Sigma}$;

4. draw ϑ from (A-30).

B   Theoretical Model

We provide the detail of our small open economies with energy sector. There is a continuum number of atomistic regions which is indexed by i in unit interval within country. As in the main text variables relate to regional indicators, where regions function as small open economies. Variables with * stand for nation wide aggregates. Small characters represent log of original variables.

B.1   Households

The representative household in a generic region maximises her life time utility, $E_t \sum_{s=t}^{\infty} \beta^{s-t} U_t$, where β $(0 < \beta < 1)$ is exogenous discount factor. Utility of individual household at time t depends on consumption C_t and labor supply N_t as follows

$$U_t = \frac{C_t^{1-\sigma}}{1-\sigma} - \frac{N_t^{1+\varphi}}{1+\varphi},$$

where the parameter σ represents risk averaging and φ measures the inverse of the Frisch elasticity of labor supply.

The basket of goods C_t is defined in the main text.

Locally produced goods in Home region ($C_{H,t}$) and imported goods from Foreign region ($C_{F,t}$) are defined over a continuum of goods as

$$C_{H,t} = \left(\int_0^1 C_{H,t}(j)^{\frac{\epsilon-1}{\epsilon}} dj \right)^{\frac{\epsilon}{\epsilon-1}},$$

and

$$C_{F,t} = \left(\int_0^1 C_{i,t}^{\frac{\gamma-1}{\gamma}} di \right)^{\frac{\gamma}{\gamma-1}}, \quad C_{i,t} = \left(\int_0^1 C_{i,t}(j)^{\frac{\epsilon-1}{\epsilon}} dj \right)^{\frac{\epsilon}{\epsilon-1}},$$

where ϵ stands for the elasticity of substitution among product varieties in the same region while γ represents the elasticity of substitution of the basket of goods produced in different regions.

The optimal consumption for each domestic basket, imported basket and individual product variety is found to be

$$C_{H,t} = \left(\frac{P_{H,t}}{P_t}\right)^{-\eta} (1 - \alpha)\, C_t,$$

$$C_{F,t} = \left(\frac{P_{F,t}}{P_t}\right)^{-\eta} \alpha C_t, \quad C_{i,t} = \left(\frac{P_{i,t}}{P_{F,t}}\right)^{-\gamma} C_{F,t},$$

$$C_{H,t}(j) = \left(\frac{P_{H,t}(j)}{P_{H,t}}\right)^{-\epsilon} C_{H,t}, \quad C_{i,t}(j) = \left(\frac{P_{i,t}(j)}{P_{i,t}}\right)^{-\epsilon} C_{i,t},$$

where $P_{H,t}(j)$ and $P_{i,t}(j)$ denote the price of a particular product produced in Home region and a generic region i, respectively. Price indices that minimise expenditures on each consumption basket are given by

$$P_t = \left[(1 - \alpha)\, P_{H,t}^{1-\eta} + \alpha P_{F,t}^{1-\eta}\right]^{\frac{1}{1-\eta}}, \tag{B-33}$$

$$P_{F,t} = \left(\int_0^1 P_{i,t}^{1-\gamma} di\right)^{\frac{1}{1-\gamma}},$$

$$P_{H,t} = \left(\int_0^1 P_{H,t}^{1-\epsilon}(j) dj\right)^{\frac{1}{1-\epsilon}}, \quad P_{i,t} = \left(\int_0^1 P_{i,t}^{1-\epsilon}(j) dj\right)^{\frac{1}{1-\epsilon}}.$$

Following Galí and Monacelli (2005), we define the *bilateral* terms of trade $S_{i,t} \equiv \frac{P_{i,t}}{P_{H,t}}$, from which we define the *effective* terms of trade as

$$S_t \equiv \frac{P_{F,t}}{P_{H,t}} = \frac{\left(\int_0^1 P_{i,t}^{1-\gamma} di\right)^{\frac{1}{1-\gamma}}}{P_{H,t}} = \left(\int_0^1 S_{i,t}^{1-\gamma} di\right)^{\frac{1}{1-\gamma}}.$$

With the above definition of the effective terms of trade and price index as found in (B-33),[29] we have the following relation around the symmetric steady state for inflation

$$\pi_t = \pi_{H,t} + \alpha \Delta s_t,$$

where $\pi_t = p_t - p_{t-1}$ and $\pi_{H,t} = p_{H,t} - p_{H,t-1}$.

---

[29]Taking log at first order, $p_t = (1 - \alpha)\, p_{H,t} + \alpha p_{F,t}$ and combined with $s_t = p_{F,t} - p_{H,t}$, we have $p_t = (1 - \alpha)\, p_{H,t} + \alpha (s_t + p_{H,t}) = p_{H,t} + \alpha s_t$. By subtracting p_{t-1} from both side, we get

$$p_t - p_{t-1} = p_{H,t} - p_{H,t-1} + \alpha (s_t - s_{t-1}).$$

It is assumed that law of one price for each goods and each basket in bilateral trade holds: $P_{i,t}(j) = P_{i,t}^i(j)$ for all $i, j \in [0,1]$. Accordingly, we have $P_{i,t} = P_{i,t}^i$ for all $i \in [0,1]$. Further from the definition of $P_{F,t} = \left(\int_0^1 P_{i,t}^{1-\gamma} di \right)^{\frac{1}{1-\gamma}}$, we have $p_{F,t} = p_t^*$ around the symmetric steady state. Combined with the definition of the terms of trade, we have

$$s_t = \pi_t^* - \pi_{H,t} \tag{B-34}$$

where $\pi_t^* = p_t^* - p_{t-1}^*$. Also the *bilateral* real exchange rate is defined as $Q_{i,t} \equiv \frac{P_{i,t}}{P_t}$, so the real effective exchange rate for a small open economy is

$$q_t \equiv \int_0^1 (p_{i,t} - p_t) \, di = p_t^* - p_t.$$

With $p_t^* = p_{F,t}$ and $p_t = (1-\alpha) p_{H,t} + \alpha p_{F,t}$,

$$
\begin{aligned}
q_t &= p_{F,t} - (1-\alpha) p_{H,t} - \alpha p_{F,t} \\
&= (1-\alpha)(p_{F,t} - p_{H,t}) \\
&= (1-\alpha) s_t.
\end{aligned}
$$

Using the above-mentioned notation, the budget constraint of a representative household in this small open economy is thus given by

$$P_t C_t + E_t [Q_{t,t+1} D_{t+1}] = D_t + W_t N_t + T_t,$$

where $Q_{t,t+1}$ is stochastic discount factor between t and $t+1$, D_t stands for nominal bond holdings, W_t represents nominal wages and T_t is the lamp-sum transfer. The household maximises the expected inter-temporal utility with respect to D_{t+1}, C_t and N_t subject to the above budget constraint for all time periods.

As a result, the Euler equation for bond holdings can be derived as

$$\beta R_t E_t \left[\left(\frac{C_{t+1}}{C_t} \right)^{-\sigma} \left(\frac{P_t}{P_{t+1}} \right) \right] = 1,$$

where $R_t = \frac{1}{E_t[Q_{t,t+1}]}$ stands for gross nominal rate.

Also the optimal condition for supplying labor is

$$C_t^\sigma N_t^\varphi = \frac{W_t}{P_t}.$$

B.2   Production

Production is detailed in the main text except firms' pricing behaviour. T

The price is assumed to be sticky à la Calvo (1983) and only a fraction of $1 - \theta$ share of firms can re-optimise their prices. Specifically, the firm maximises the following sum of expected discounted profits by setting $P'_{H,t}$

$$E_t \sum_{s=0}^{\infty} \theta^s Q_{t,t+s} Y_{t+s} \left[P'_{H,t} - MC_{t+s} \right].$$

The first order condition gives

$$E_t \sum_{s=0}^{\infty} (\beta\theta)^s P_{t+s}^{-1} C_{t+s}^{-\sigma} Y_{t+s} \left[P'_{H,t} - \frac{\epsilon}{\epsilon - 1} MC_{t+s} \right].$$

Around the symmetric steady state, the above expression can be rewritten as

$$\pi_{H,t} = \beta E_t \left[\pi_{H,t+1} \right] + \lambda \widehat{mc}_t,$$

where $\widehat{mc}_t \equiv (mc_t - p_{H,t}) - (mc - p_H)$ is the log of real marginal cost defined in terms of domestic price and $\lambda \equiv \frac{(1-\theta)(1-\beta\theta)}{\theta}$.[30]

B.3 International Financial Market and General Equilibrium

In equilibrium, all firms within a small open economy behave in the same way. So $Y_t = Y_t(j)$, $N_t = N_t(j)$, $\mathfrak{E}_t = \mathfrak{E}_t(j)$. It is assumed that asset markets are complete within country. This implies

$$C_t = C_t^i Q_{i,t}^{\frac{1}{\sigma}}, \tag{B-35}$$

where $Q_{i,t}$ stands for the bilateral real exchange rate which is defined as $Q_{i,t} \equiv \frac{P_{i,t}}{P_t}$. Using lower case letters for log variablesand iterating over i, we have[31]

$$c_t = c_t^* + \left(\frac{1-\alpha}{\sigma} \right) s_t. \tag{B-36}$$

The above is the perfect risk sharing condition in effective terms.

---

[30]$\widehat{mc}_t$ gives the same dynamics at first order as $mc_t - p_{H,t}$.
[31]Taking the log in both side of (B-35),

$$c_t = c_t^i + \frac{1}{\sigma} q_{i,t}.$$

Integrating over i (considering of effective risk sharing), we have

$$\begin{aligned} c_t &= \int_0^1 c_t^i di + \frac{1}{\sigma} \int_0^1 q_{i,t} di \\ &= c_t^* + \frac{1}{\sigma} q_t \\ &= c_t^* + \left(\frac{1-\alpha}{\sigma} \right) s_t. \end{aligned}$$

Good markets clear for a typical good j with

$$Y_t(j) = C_{H,t}(j) + \int_0^1 C_{H,t}^i(j)di$$

By plugging the demand found previously, combined with the above complete market condition and taking the first-order approximation around the symmetric steady state, we have[32]

$$y_t = c_t + \frac{\alpha\omega}{\sigma}s_t, \tag{B-37}$$

where $\omega \equiv \sigma\gamma + (1-\alpha)(\sigma\eta - 1)$.

Further, good market clearing (B-37) and (B-36) provide the following equation[33]

---

[32]Noting that demand from country i for goods produced in H, $C_{H,t}^i(j)$,

$$C_{i,t}(j) = \left(\frac{P_{i,t}(j)}{P_{i,t}}\right)^{-\epsilon} C_{i,t}, \; C_{i,t} = \left(\frac{P_{i,t}}{P_{F,t}}\right)^{-\gamma} C_{F,t} \text{ and } C_{F,t}^i = \left(\frac{P_{F,t}^i}{P_t^i}\right)^{-\eta} \alpha C_t^i$$

$$C_{H,t}^i(j) = \left(\frac{P_{H,t}(j)}{P_{H,t}}\right)^{-\epsilon} \left(\frac{P_{H,t}}{P_{F,t}^i}\right)^{-\gamma} \left(\frac{P_{F,t}^i}{P_t^i}\right)^{-\eta} \alpha C_t^i$$

$$Y_t(j) = \left(\frac{P_{H,t}(j)}{P_{H,t}}\right)^{-\epsilon} \left[\left(\frac{P_{H,t}}{P_t}\right)^{-\eta}(1-\alpha)C_t + \int_0^1 \left(\frac{P_{H,t}}{P_{F,t}^i}\right)^{-\gamma}\left(\frac{P_{F,t}^i}{P_t^i}\right)^{-\eta}\alpha C_t^i di\right]$$

Plugging the above in the definition of aggregate output such as $Y_t = \left(\int_0^1 Y_t(j)^{\frac{\epsilon-1}{\epsilon}}dj\right)^{\frac{\epsilon}{\epsilon-1}}$,

$$Y_t = \left(\int_0^1 \left(\frac{P_{H,t}(j)}{P_{H,t}}\right)^{-\epsilon\frac{\epsilon-1}{\epsilon}} cst^{\frac{\epsilon-1}{\epsilon}}dj\right)^{\frac{\epsilon}{\epsilon-1}} = \left(\frac{\int_0^1 P_{H,t}^{1-\epsilon}(j)di}{P_{H,t}}\right)cst$$

$$= \left(\frac{P_{H,t}}{P_t}\right)^{-\eta}(1-\alpha)C_t + \int_0^1 \left(\frac{P_{H,t}}{P_{F,t}^i}\right)^{-\gamma}\left(\frac{P_{F,t}^i}{P_t^i}\right)^{-\eta}\alpha C_t^i di$$

Plugging the demand and with complete asset market condition,

$$Y_t = \left(\frac{P_{H,t}}{P_t}\right)^{-\eta}(1-\alpha)C_t + \int_0^1 \left(\frac{P_{H,t}}{P_{F,t}^i}\right)^{-\gamma}\left(\frac{P_{F,t}^i}{P_t^i}\right)^{-\eta}\alpha C_t^i di$$

$$= \left(\frac{P_{H,t}}{P_t}\right)^{-\eta}\left[(1-\alpha)C_t + \int_0^1 \left(\frac{P_{H,t}}{P_{F,t}^i}\right)^{\eta-\gamma}\left(\frac{P_t}{P_t^i}\right)^{-\eta}\alpha C_t^i di\right]$$

$$= \left(\frac{P_{H,t}}{P_t}\right)^{-\eta}C_t\left[(1-\alpha)C_t + \alpha\int_0^1 S_{i,t}^{\gamma-\eta}Q_{i,t}^{\eta-\frac{1}{\sigma}}di\right]$$

where for the last equality we have used the definition of bilateral terms of trade, bilateral real exchange rate and bilateral risk sharing condition as $S_{i,t} \equiv \frac{P_{i,t}}{P_{H,t}}$, $Q_{i,t} \equiv \frac{P_{i,t}}{P_t}$ and $C_t = C_t^i Q_{i,t}^{\frac{1}{\sigma}}$.

[33]The above market clearing condition holds for a generic region i as $y_t^i = c_t^i + \frac{\alpha\omega}{\sigma}s_t^i$.
Iterating over i, we have

$$\int_0^1 y_t^i di = \int_0^1 c_t^i di + \frac{\alpha\omega}{\sigma}\int_0^1 s_t^i di$$

$$= c_t^*.$$

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$$y_t = y_t^* + \frac{1}{\sigma_a} s_t,$$

where $\sigma_a \equiv \frac{\sigma}{(1-\alpha)+\alpha\omega}$.

With energy market clearing in the main text, the system is completed by specifying the following national level of inflation dynamics and marginal cost:

$$\pi_t^* = \beta E_t \left[\pi_{t+1}^* \right] + \lambda \left(mc_t^* - p_t^* \right).$$

Since the whole nation consist of a part of the rest of the world for a small open economy, there is no distinction between regional trade and international trade. We define real net exports at first order approximation measured in domestic output following Galí and Monacelli (2005)

$$nx_t = y_t - c_t - \alpha s_t.$$

Also nominal expenditure on imported goods for a small open economy is

$$P_{F,t} C_{F,t} = \left(\frac{P_{F,t}}{P_t} \right)^{1-\eta} \alpha P_t C_t = \left(\frac{S_t P_{H,t}}{P_t} \right)^{1-\eta} \alpha P_t C_t.$$

Thus real imports is given by

$$M_t \equiv \frac{P_{F,t} C_{F,t}}{P_{H,t}} = S_t^{1-\eta} \left(\frac{P_{H,t}}{P_t} \right)^{-\eta} \alpha C_t.$$

With its first order we have

$$m_t = (1 - \eta) s_t - \eta \left(p_{H,t} - p_t \right) + c_t.$$

Real exports at first order approximation is thus given by

$$x_t = nx_t + m_t$$

The shocks and monetary policy were given in the main text.

The whole (log-linear) system is summarised in Table B-1.

Since $\int_0^1 s_t^i di = 0$ so $y_t^* \equiv \int_0^1 y_t^i di = c_t^* \equiv \int_0^1 c_t^i di$. Together with $y_t^* = c_t^*$ and (B-37) and (B-36), we have

$$y_t = c_t^* + \left(\frac{1-\alpha}{\sigma} \right) s_t + \frac{\alpha\omega}{\sigma} s_t$$

$$= y_t^* + \left(\frac{(1-\alpha) + \alpha\omega}{\sigma} \right) s_t.$$

Table B-1: The Model

Price indices	$\pi_t = \pi_{H,t} + \alpha \Delta s_t$
National inflation	$\Delta s_t = \pi_t^* - \pi_{H,t}$
Euler equation	$r_t = \sigma \left(E_t \left[c_{t+1} \right] - c_t \right) - E_t \left[\pi_{t+1} \right]$
New Keynesian Phillips curve	$\pi_{H,t} = \beta E_t \left[\pi_{H,t+1} \right] + \lambda \left(mc_t - p_{H,t} \right)$
National output	$y_t = y_t^* - \frac{1}{\sigma_a} s_t$
Goods market clearing	$y_t = c_t + \frac{\alpha \omega}{\sigma} s_t$
Optimal labor supply	$w_t - p_t = \sigma c_t + \varphi n_t$
Definition of net export	$nx_t = \alpha (\frac{\omega}{\sigma} - 1) s_t$
Import	$m_t = (1 - \eta) s_t - \eta \left(p_{H,t} - p_t \right) + c_t$
Export	$x_t = nx_t + m_t$
Definition of producer inflation	$\pi_{H,t} = p_{H,t} - p_{H,t-1}$
Definition of inflation	$\pi_t = p_t - p_{t-1}$
Definition of world inflation	$\pi_t^* = p_t^* - p_{t-1}^*$
Monetary Policy	$r_t = \phi_p \pi_t^*$
Labor demand	$n_t = - \left(w_t + mc_t \right) + y_t$
Energy market clearing	$e_t^* = \mu \left(w_t - p_{e,t} \right) + y_t^*$
Marginal cost	$mc_t = \mu w_t + (1 - \mu) p_{e,t} - a_t$
National inflation	$\pi_t^* = \beta E_t \left[\pi_{t+1}^* \right] + \lambda \left(mc_t^* - p_t^* \right)$

## B.4   Calibration and Impulse Response Functions

We calibrate the model with the following parameters' values as in Table B-2.

Impulse response functions of all variables following local productivity shock and output shock in other regions are found in Figure B-1 and Figure B-2, respectively.

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Table B-2: Calibration of the model

β	Discount factor	0.99
φ	Inverse of Frisch elasticity of labor supply	3
σ	Risk aversion	2
η	Elasticity between local and imported goods	1
γ	Elasticity of substitution across region	1
θ	Calvo price revision	0.92
α	Consumption Openness	0.4
μ	Non-Energy Share	0.91
ϕ_π	Taylor rule	1.5
ρ_{y^*}	Persistence of national output	0.1
ρ_{e^*}	Persistence of energy supply	0.9
ρ_a	Persistence of local productivity	0.1

Figure B-1: IRFs of 1% decrease in regional productivity
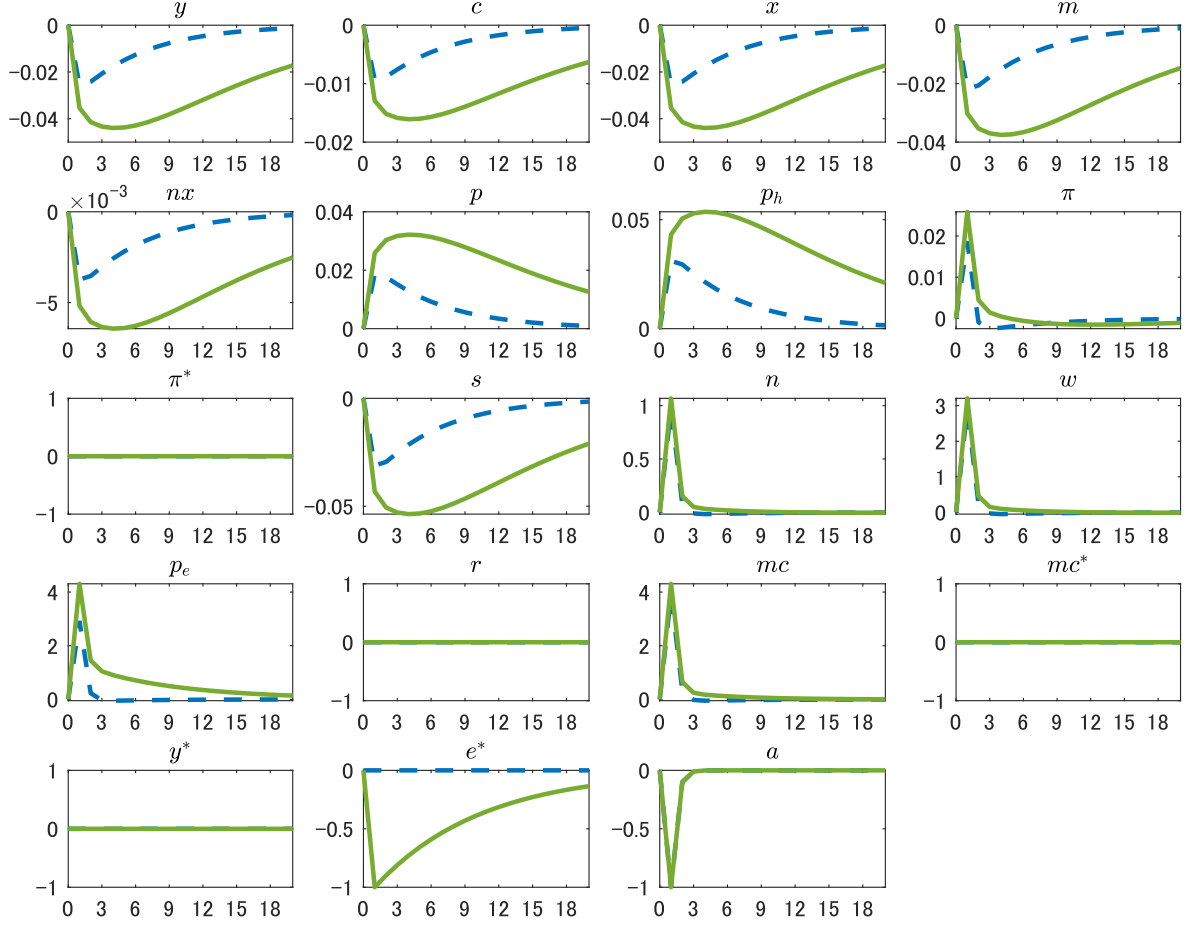
Impulse responses from a shock in (a) regional productivity, $\varepsilon_{a,t}$ and energy supply $\varepsilon_{e^*,t}$, which can be used to approximate one hit region; (b) output in other regions, $\varepsilon_{y^*,t}$ and energy supply $\varepsilon_{e^*,t}$, which can be used to approximate for non-hit regions. The green solid line presents the benchmark case where (a) the regional shock and energy supply shock take simultaneously; (b) the shock on output in other regions and energy supply shock take simultaneously. The blue dashed line represents the same productivity shock with zero persistence of energy supply shock.

Figure B-2: IRFs of 1% decrease in nationwide output
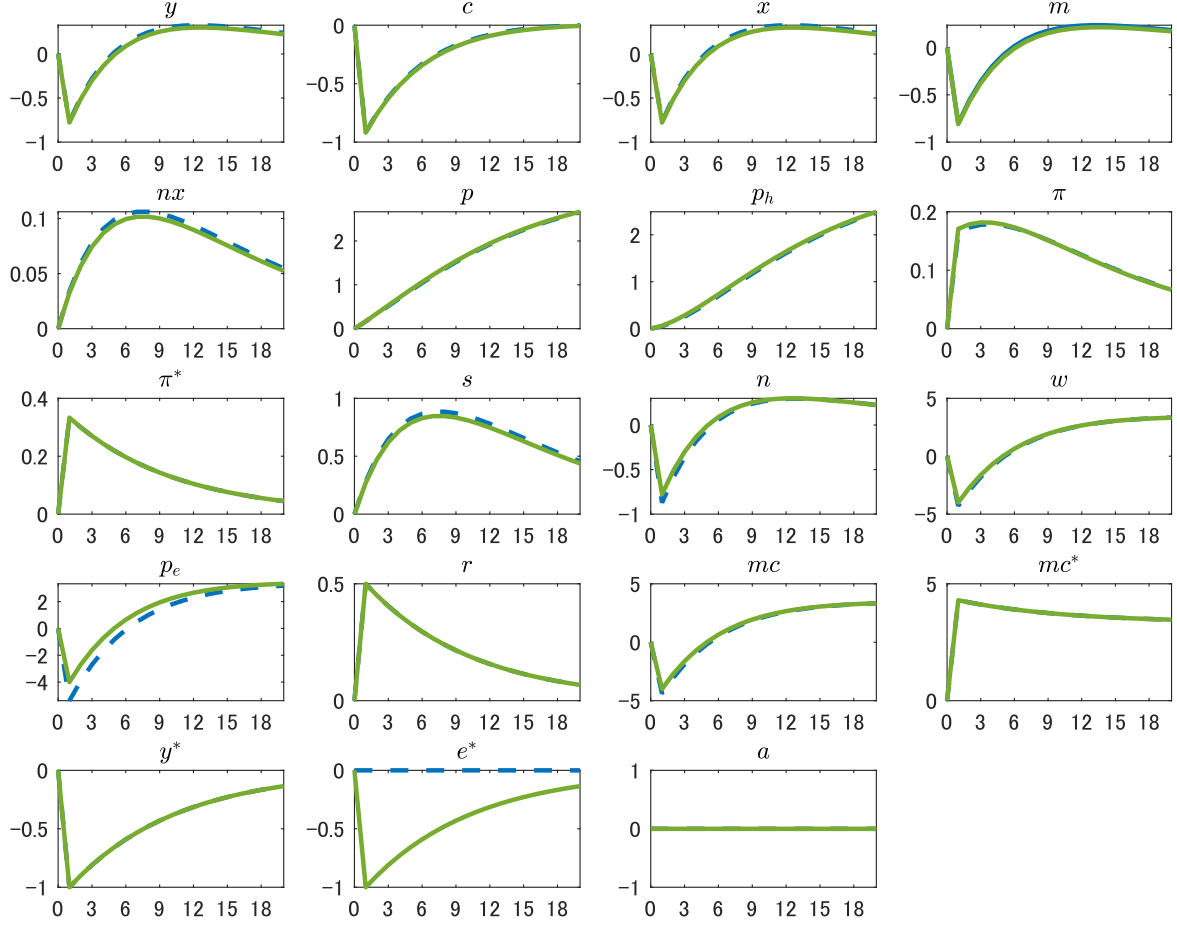
Impulse responses from a shock in (a) regional productivity, $\varepsilon_{a,t}$ and energy supply $\varepsilon_{e^*,t}$, which can be used to approximate one hit region; (b) output in other regions, $\varepsilon_{y^*,t}$ and energy supply $\varepsilon_{e^*,t}$, which can be used to approximate for non-hit regions. The green solid line presents the benchmark case where (a) the regional shock and energy supply shock take simultaneously; (b) the shock on output in other regions and energy supply shock take simultaneously. The blue dashed line represents the same productivity shock with zero persistence of energy supply shock.

C   Additional Empirical results

C.1   Confidence bands of conditional forecasts

Figure C-3: Scenario analysis - Forecasts based on actual electricity supply
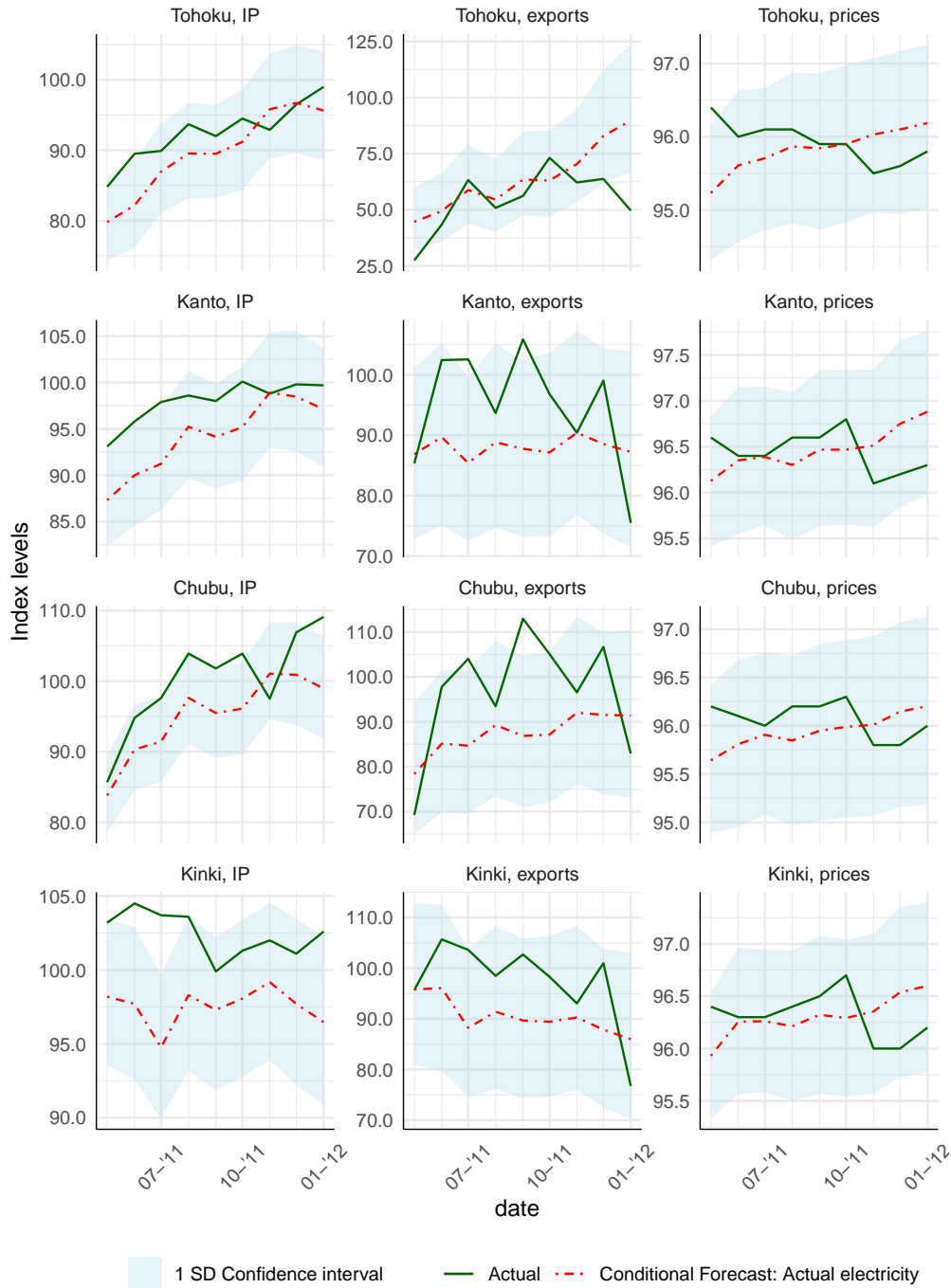
Note: Conditional forecast based on a BPVAR model, as described in the text. Actual represents observed data, while conditional forecast represents the median response of the forecast using observed total energy supply, as provided in Figure 7.

Figure C-4: Scenario analysis - Forecasts based on counterfactual electricity supply
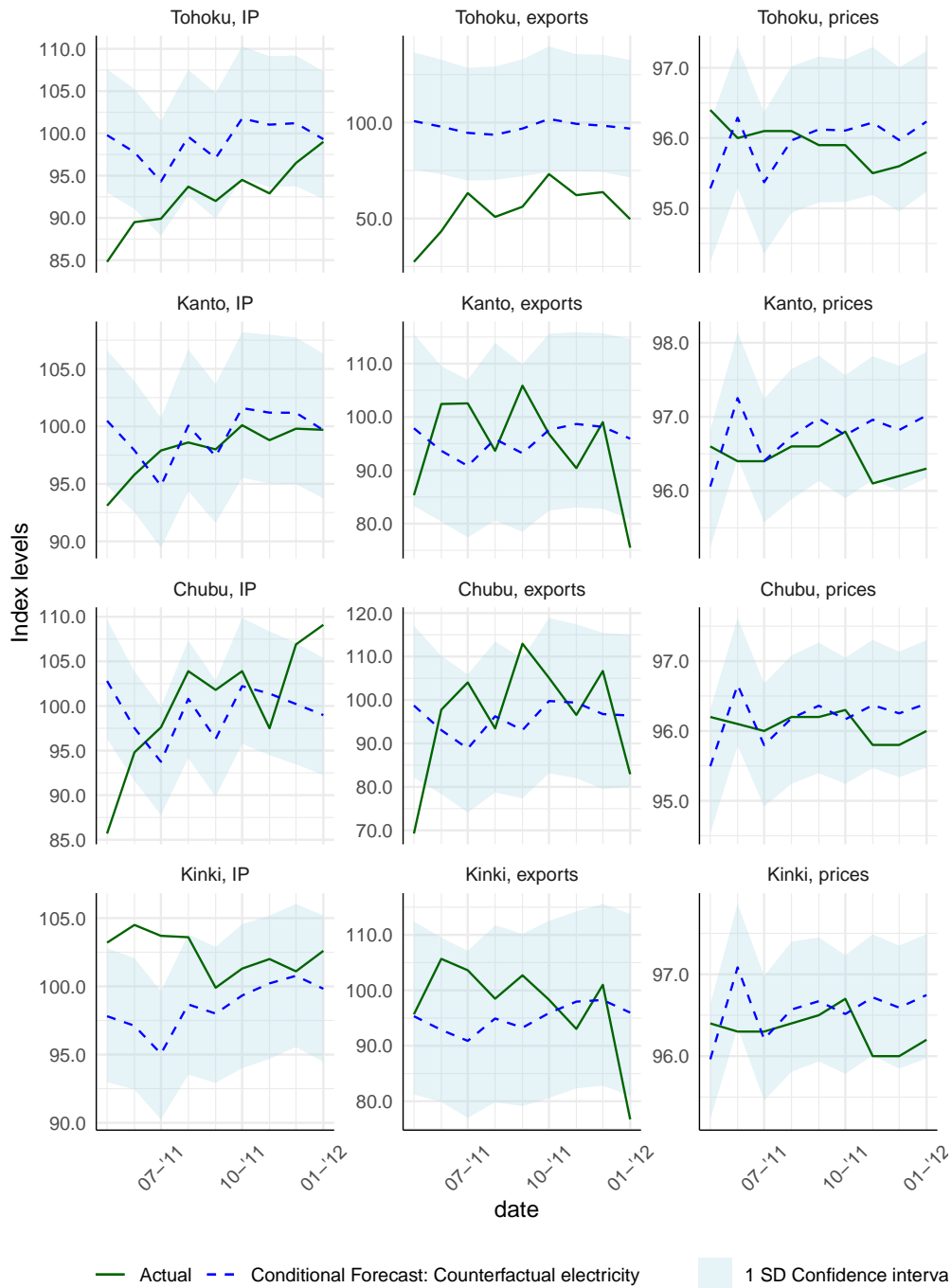
Note: Conditional forecast based on a BPVAR model, as described in the text. Actual represents observed data, while condition forecast represents the median response of the forecast using a counterfactual path of total energy supply, as provided in Figure 7.