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Analyzing the indirect effects of nature-related shocks on the economy: Methodological approaches and insights*

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Abstract

This paper defines nature-related shocks as nature degradation and other changes in the availability and quality of ecosystem services (e.g., soil degradation and biodiversity loss) and discusses ways to introduce them into frameworks of shock propagation, with particular attention to their spillover effects (for example across regions and sectors). We think of nature-related shocks as an extension of "classic" environmental shocks (such as changes in weather and climate, and natural disasters) which have been considered in the existing literature to some degree. We first review approaches commonly used in the literature to investigate how shocks generate cascading effects throughout the economy. We focus on firm-level supply chain analysis, local projections, structural vector autoregressive models and production network models. We then discuss options to integrate nature-related shocks into these existing frameworks, as well as the main challenges and ways forward in this context.

Keywords: Nature-related shocks, firm-level supply chain analysis, structural vector autoregressive models, production network models, local projections.

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1 Introduction

Modern economies are characterized by large within and between interdependencies. Within economies, sectors are connected, for instance, through supply chain linkages and consumption complementarities. Between economies, trade drives countries closer together, independent of their geographic location. This interconnectedness means that shocks occurring at one specific node (e.g., to a firm or sector) not only lead to *direct effects* at the respective point of occurrence, but can generate cascading *indirect effects* that propagate through the entire system and generate non-negligible impacts on a higher, macroeconomic level (e.g., Gabaix 2011; Acemoglu et al. 2012; Carvalho 2014; Tintelnot et al. 2018; Baqaee and Farhi 2019). Understanding this transmission of shocks is crucial for empirically capturing and quantifying their full macroeconomic implications.

This paper defines shocks related to nature degradation and changes in the availability and quality of ecosystem services as nature-related shocks. These shocks can be broadly categorized as acute or chronic, depending on their speed and persistence (see NGFS 2023). Examples include changes in water quality, soil degradation, and biodiversity loss.[1] These shocks have not received much attention in the literature on shock propagation through the economy, even though they appear likely to exert, akin to economic shocks, a significant influence on various economic variables. For example, they seem to have the potential to trigger a multitude of adverse consequences such as productivity loss, price increases, and amplified economic uncertainty, which can, in turn, have repercussions across many companies, sectors, and regions (e.g., see Ceglar et al. 2024; Ranger et al. 2024). Moreover, nature-related shocks are inherently endogenous, which adds a layer of complexity to analyzing their economic impact: they often emerge from within the complex dynamics of the natural

[1] Note that these nature-related shocks are closely related to shocks to weather, climate, and natural disasters, which have been considered in economic research on shock propagation to some degree. In this project, we explicitly focus on shocks that are distinct from those. For a more detailed definition, see chapter 2.

environment and the economic system (Brausmann and Bretschger, 2024). Consequently, unraveling the precise implications of these shocks is an ambitious task.

In light of this, the goal of this paper is twofold. First, we survey the existing literature on methods aimed at understanding the cascading effects of shocks throughout the economy. To this end, we review four approaches: (1) Firm-level supply chain analysis, (2) Local projections (LPs), (3) Structural vector autoregressive models (SVARs), and (4) Production network models (PNMs). We focus on these given their prevalence in the existing literature on macroeconomic shock propagation and our prior belief that they represent the most suitable methodologies to be extended to the investigation of nature-related shocks. Firm-level supply chain analysis relies on information about linkages among individual firms to trace how the effect of shocks impacting a company propagates to its (direct and indirect) suppliers and customers. In local projections (LPs) the dynamic relationships between variables are incorporated into a reduced-form approach to investigate the impact of shocks on the economic system linking macroeconomic variables such as output, inflation, employment, and other key aggregates. Structural Vector Autoregressive models (SVARs) allow for the identification of structural shocks and the analysis of their full impact (both direct and indirect) on the system over time by embedding economic structure into the model through theoretically motivated restrictions on contemporaneous interactions across variables and their dynamic responses over time. Production network models (PNM) enable the analysis of how shocks propagate through an economy represented as a network of interlinked sectors connected via input–output relationships, thereby capturing the aggregate effects of shocks within a general equilibrium framework.[2] To the best of our knowledge, these approaches have been used to investigate the propagation of climate and weather changes and natural disasters (as discussed in the following chapters), but, with few exceptions, have not been extended to nature-related shocks. Hence, our second goal for this paper is to discuss ways to apply these

[2]We provide references and discuss key contributions to each method in the sections that follow.

existing methods to nature-related shocks.

Recent advancements in the availability of data have facilitated a wide range of empirical and quantitative analyses to understand the transmission of shocks through the economy. For instance, datasets on firms' production networks contain increasingly granular details on the linkages between firms and sectors, making them appropriate to study the propagation of shocks in the economy (Carvalho and Tahbaz-Salehi, 2019; Baqaee and Rubbo, 2022). In addition, novel data on ecosystem services such as soil quality and biodiversity (e.g., Dasgupta et al. 2024, World Bank 2025) promise to enable detailed tracking of nature-related events, and consequently, their transmission and economic impacts. Hence, we consider this a particularly suitable point in time for this review.

The paper is structured as follows. Section 2 defines the shocks we focus on in this article in more detail. Section 3 reviews how firm-level supply chain analysis, LPs, SVARs, and PNMs have been used in the literature to capture the propagation of shocks. For each methodology, we also discuss how it could be applied to understand the transmission of nature-related shocks through the economy and highlight some opportunities and challenges going forward. Section 4 concludes.

2 Definition: Nature-Related Shocks

The NGFS (2023) defines nature-related financial risks as *"[...] risks of negative effects on economies, individual financial institutions and financial systems that result from: i. the degradation of nature, including its biodiversity, and the loss of ecosystem services that flow from it (i.e., physical risks); or ii. the misalignment of economic actors with actions aimed at protecting, restoring, and/or reducing negative impacts on nature (i.e., transition risks)."* (p. 9)

Following this definition, we characterize nature-related shocks as the processes of nature degradation and other changes in the availability and quality of ecosystem services (e.g., water and soil) that can affect economies.[3] Nature-related shocks include both physical risks (e.g., deterioration or loss of the flow of ecosystem services to economic activities) and transition risks (e.g., restriction in the availability of ecosystem services through regulation) (Ranger et al., 2024). While nature degradation and changes in ecosystem services can be triggered or influenced by natural phenomena, such as climate change (NGFS, 2023), our focus is on the resulting degradation and disruption in the provision of ecosystem services rather than the natural events themselves. Furthermore, environmental shocks related to climate change (mostly climate and weather shocks, and natural disasters) have already been more commonly studied in the economics literature. Accordingly, we exclude them from our definition of nature-related shocks.

The concept of a "shock" in this review aligns with the standard macroeconomic view of shocks as exogenous stimuli or surprises that trigger responses between interconnected variables (Blanchard and Quah, 1989). A shock represents an innovation (unexpected and independent of past dynamics) that allows an assessment of its causal impact. Even if a disturbance originates within the system, it must appear as an unexpected irregularity rather than a part of the predetermined evolution.[4] Consequently, to examine nature-related shocks, an exogenous approximation to these shocks must be identified. That is, shocks must be approximated as unanticipated changes orthogonal to all key components of a system. This can be challenging as nature-related shocks are inherently endogenous (i.e., they often stem from interactions of human, nature, and economic features of a system, e.g., Brausmann and Bretschger 2024). However, several approaches allow for the reconciliation of the systemic origins of nature-related shocks with the requirements for exogenous shocks in macroeconomic analyses. We discuss some of them in this review.

[3]Note that these are often slow-moving processes and hence the term "shock" might be slightly misleading. However, in this review, we retain the term given the possibility of constructing nature-related shock series from time series data on gradual developments, which can then be analyzed using standard tools for studying economic shocks and their transmission.

[4]This definition aligns with the concept of shocks commonly adopted in the macroeconomics literature (e.g., Bernanke 1986).

Further, the methods we consider in this article cover both the investigation of shocks on the macro level (e.g., changes in water quality impacting a large region) and idiosyncratic shocks affecting single firms or sectors (e.g., very localized degradation of soil quality). As discussed in a relatively recent literature, this distinction is increasingly seen as blurred, since idiosyncratic shocks can, under certain conditions, aggregate up and generate macroeconomic fluctuations (e.g., Gabaix 2011; Grigoli et al. 2023; Debortoli and Galí 2024). The suitability of different methods for analyzing a particular shock depends on the nature of the shock, which will become more evident as we examine each approach in detail. We will introduce the approaches and their potential to be applied to nature-related shocks in the next section.

3 Approaches

In this section, we review approaches that can help to understand the propagation of the effects of a shock through the economy. After introducing each methodology, we discuss how it can be adjusted to account for nature-related shocks, identify challenges that may arise, and, if possible, suggest potential solutions.

3.1 Firm-level supply chain analysis

Firm-level supply chain analysis uses granular data to document the propagation of shocks at the firm level, considering customers and suppliers of the firms directly hit by the shock (Barrot and Sauvagnat, 2016; Boehm et al., 2019; Pankratz and Schiller, 2021; Balboni et al., 2023; Forslid and Sanctuary, 2023; Demir et al., 2024), and sometimes also firms that are indirectly linked, for instance, the customer of a customer whose supplier was hit (Inoue and Todo, 2019; Carvalho et al., 2021; Kashiwagi et al., 2021). These analyses show that in the event of a shock, individual firms suffer productivity losses that are passed on to other firms. Hence, ultimately, the propagation of shocks often occurs at the firm level, making it useful to understand the propagation mechanism at this level of granularity.

As illustrated in the examples mentioned above, the overall goal of firm-level supply chain analyses is to understand the cascading effects of shocks that affect individual companies. A general structure of this reduced-form approach consisting of three steps emerges: (1) identify an exogenous shock and affected companies; (2) link the affected companies to their suppliers or customers; (3) trace the disruption caused by the shock along the linkages between companies. Firm-level supply chain analysis is particularly useful for identifying causal effects of shocks (such as localized natural disasters), as these are often arguably exogenous at the company level. Given the considerable variation in firms' exposure to the shock, endogeneity concerns that arise at more aggregated levels (e.g., at the sectoral level) can be resolved (Carvalho and Tahbaz-Salehi, 2019).

To our knowledge, there are no existing studies that specifically examine the transmission of nature-related shocks through supply chains at the firm level. However, prior research has investigated the propagation of other environmental shocks, such as natural disasters and extreme weather events, within supply chain networks. For instance, Barrot and Sauvagnat (2016) evaluate the impact of natural disasters on firms' sales growth in the US and show that customers of hit suppliers experience a 2–3 percentage point drop in sales growth, around 25% below average, and a 1% decline in market value. These effects are temporary, concentrated in active relationships, and amplified when inputs are differentiated or patented, illustrating how input specificity drives shock transmission through production networks. Boehm et al. (2019) extend this analysis globally, showing that US firms dependent on Japanese suppliers faced steep output losses following the 2011 Japanese earthquake, consistent with low substitutability across inputs. More precisely, they find that US affiliates of Japanese multinationals experienced a roughly one-for-one decline in output in response to declines in Japanese imports, indicating that the short-run elasticity of substitution between imported and domestic inputs is close to zero. Similarly, Forslid and Sanctuary (2023) investigate the effects of the 2011 flood in Thailand through a supply chain lens. They find that Swedish firms sourcing inputs from flood-affected suppliers experienced a substantial and persistent decline in output, disproportionate to the relatively short duration of the production disruptions in Thailand. Pankratz and Schiller (2021) examine the impact of physical climate risks on firms' financial performance and supply chain management. They show that natural disasters not only reduce the operating performance (revenues and operating income scaled by assets) of suppliers and their customers but can also lead to the termination of supply chain relationships. Balboni et al. (2023) focus on the occurrence of extreme weather events in Pakistan and find that firms affected by major floods relocate to less flood prone areas, diversify their supplier base, and shift the composition of their suppliers towards those located in less flood-prone regions and reached via less flood-prone roads.

While the studies above provide evidence for the propagation of shocks from a firm to its direct suppliers and customers, more detailed information on the interconnectedness of firms, including those that are more distant and indirectly connected to the initial shock, helps understand the broader impact of these shocks on the overall economy. To this end, Carvalho et al. (2021) introduce additional layers of relationships, and look at the negative impact caused by the Great East Japan Earthquake and tsunami of 2011 on direct, but also indirect customers and suppliers of affected firms, i.e., those linked through multi-tier supply chain relationships. Using firm-level supply chain data, they find that indirectly connected firms also experienced significant output declines after the natural disaster. Their findings highlight the indirect propagation effects of localized disturbances, emphasizing that even if the individual, firm-level impact of the disruption may not be substantial, particularly for indirectly exposed firms, its cumulative effect can be significant.[5] Inoue and Todo (2019) obtain similar results when modeling the potential impact of a future earthquake based on the impacts of the Great East Japan Earthquake 2011: they find that the indirect effects of the natural disaster on production due to the propagation of the shock across supply

[5]In addition to these reduced-form supply chain analyses, Carvalho et al. (2021) also estimate a general equilibrium model, see section 3.4.

chains are substantially larger (10.6% of GDP) than their direct effects (0.5% of GDP). Lastly, Kashiwagi et al. (2021) investigate the geographic transmission of the economic effects of natural disasters along supply chains, capturing both direct and indirect links across regions, with a particular focus on heterogeneity by network characteristics. They identify input specificity and network density as important determinants of shock transmission in the context of the US.

Overall, these studies highlight the far-reaching consequences of shocks in supply chains, demonstrating the importance of considering both direct and indirect linkages to understand the impact on the broader economy comprehensively.

Application to nature-related shocks

The framework used to analyze how the impact of shocks propagates from affected firms to their upstream and downstream supply chains could, in principle, be extended to nature-related shocks. However, at least two challenges arise.

First, datasets on supply chain relationships often have geographically limited coverage, typically concentrated in developed countries. While this presents a general limitation to supply chain analyses, it poses a particular challenge in the context of nature-related shocks, where data constraints are exacerbated due to the location specificity of nature degradation and changes in ecosystem services, with more frequent occurrences in regions underrepresented in existing datasets. In this context, case studies can provide important insights, but their findings are often difficult to generalize due to concerns over external validity. For instance, in a recent case study, Robeco, in collaboration with the Cambridge Institute for Sustainability Leadership, conducted a stress test to measure the impact of soil degradation in Brazil on the financial risks of listed companies (University of Cambridge Institute for Sustainability Leadership and Robeco, 2023). Importantly, the study finds not only negative effects on the financial performance of firms directly affected by soil degradation, but also smaller food companies sourcing from degraded areas experience significant valuation drops, highlighting the material risk of soil health to supply chain stability (University of Cambridge Institute for Sustainability Leadership and Robeco, 2023). However, as previously stated, drawing conclusions from this specific case study to other contexts may be challenging due to location-specific climate, crop mix, land use practices, and economic conditions, which may not be representative of agricultural systems elsewhere. Moreover, the study focuses on financial outcomes in one sector, limiting its direct applicability to non-agricultural or differently structured supply chains.

Second, supply chain analyses are based on successfully identifying a shock, which consequently allows for the identification of causal relationships. However, nature degradation usually happens gradually over time (at least until a tipping point occurs), making the identification of a shock more challenging. One approach to identify shocks that occur gradually would be to define a shock based on specific behaviors of the corresponding nature degradation time-series, such as showing large deviations from the mean of regression residuals (this has also been done in the context of local projections, see section 3.2). For instance, Kahn et al. (2021) use deviations of temperature and precipitation from their historical norms to study the long-term impact of climate change on economic activity across countries. Other authors have worked with orthogonalized residuals obtained from regressing the variable of interest (in our case, the nature-related change) on lags of itself and other variables that could predict its future path (see e.g. Meinerding et al. 2023; Colesanti Senni et al. 2024). Even though neither of these papers is in the context of supply chains, they provide interesting insights into potential ways to construct shock series for nature degradation data, which is crucial to extend the methodology of supply chain analysis to nature-related shocks.

3.2 Local Projections

Local projections (LPs) have frequently been applied to study the macroeconomic impact of economic shocks, e.g., to fiscal policy (e.g., Auerbach and Gorodnichenko 2012; Ramey and

Zubairy 2018; Born et al. 2020a), monetary policy (e.g., Tenreyro and Thwaites 2016; Paul 2020; Miranda-Agrippino and Ricco 2021), and credit (e.g., Jordà et al. 2013).

In the empirical macroeconomics literature, local projections have received increasing attention since their introduction in Jordà (2005). As another reduced-form approach, local projections impose relatively little structure and allow the researcher to recover valid model predictions without specifying the underlying, true data-generating process well (Jordà, 2005). In contrast to the more structural models discussed below (see 3.3 and 3.4), LPs do not require a dynamically consistent system, nor do they assume a particular autoregressive structure in the data. Hence, they allow the data to determine the shape of impulse response functions (IRFs) and do not force them to have a specific pre-determined functional form.

LPs estimate IRFs directly by running regressions of the outcome of interest in each future period $h \in H$:

$$y_{t+h} = \alpha_h + \beta_h Z_t + \gamma_h' \mathbf{X}_t + \epsilon_{t+h} \tag{1}$$

Here, y_{t+h} describes the outcome of interest, for instance GDP growth, in period $t+h$. β_h denotes the main coefficient of interest capturing the impact of the shock Z_t in period h on the outcome. α_h is a horizon-specific constant and γ_h measures the horizon-specific effect of the control variables $\mathbf{X}_t$. Importantly, this vector of controls can accommodate lags of y and Z to flexibly capture the dynamic structure of the system. ϵ_{t+h} denotes the error term at horizon h. By estimating regression 1 at different horizons $h \in H$, we obtain a series of coefficients $\beta_0, \beta_1, ..., \beta_H$ which describe the impulse response function of y to shock Z_t over time.

Despite the simplicity of the method vis-à-vis a fully specified structural model, there are several critical methodological choices to make when implementing LPs. First, the estimation method is typically Ordinary Least Squares but can be adjusted, for instance to account for endogeneity concerns and complex model dynamics including non-linearities and state-dependence by incorporating Instrumental Variables/ Generalized Method of Moments, Bayesian methods or state-dependent models (for a detailed methodological review, see Jordà and Taylor 2025). Second, the choices of forecast horizon H, control variables $\mathbf{X}$, and number of lags are important to capture all relevant components of the dynamic response to the investigated shock in the model (Montiel Olea and Plagborg-Møller, 2021).

Lastly, the identification method of the shock itself is crucial in the context of local projections, as, in contrast to more structural models like vector autoregressive models (VARs), LPs do not recover shocks from the data but require an already identified shock as input. There are different methods to identify shocks. First, narrative accounts of policy changes can be employed to construct a series of shocks to be investigated (e.g., Tenreyro and Thwaites 2016; Ramey and Zubairy 2018). This narrative approach, first developed notably in Ramey and Shapiro (1998), was used by Romer and Romer (2004), and Romer and Romer (2010) to identify exogenous shocks using narrative records such as presidential speeches, congressional reports, and internal policy documents. The key idea is to isolate policy changes that are unexpected and not driven by current economic conditions, often by controlling for internal forecasts and anticipated developments. Second, high-frequency identification leverages high-frequency (often financial) data to isolate unexpected events and derive shock series based on them (most notably employed in monetary policy settings, e.g., Kuttner 2001; Gurkaynak et al. 2005). Rather than assuming those to reflect the true shocks themselves, the series is often used as an external instrument for the underlying shock (e.g., Paul 2020; Miranda-Agrippino and Ricco 2021). Lastly, shocks can be identified if they are (assumed to be) exogenous themselves. For example, Born et al. (2020a) rely on the widely accepted assumption that government consumption is predetermined within a given quarter.

Local projections have been used, especially recently, to consider the economic impact of environmental shocks. For instance, Bilal and Känzig (2024) estimate the consequences of global temperature shocks on world GDP using LPs. The authors define a shock as instances where global temperature deviates from its long-run trend in global mean temperature and find that the macroeconomic damages due to climate change are significantly larger than expected from prior analyses. Using the LP method to trace out IRFs of real per capita GDP, Acevedo et al. (2020) find that rising global temperatures disproportionately harm low-income countries (especially those already experiencing hot climates) by reducing agricultural output, productivity, capital accumulation, and health, thus significantly lowering per capita GDP. Using LPs across 173 countries, Cevik and Jalles (2024) find that weather-related climate shocks significantly affect inflation and economic growth, with temperature shocks generally reducing inflation, while droughts and storms increase it. Furthermore, they find that adverse impacts on growth are persistent and severe in developing countries, but negligible in advanced economies (Cevik and Jalles, 2024).

Given the reduced-form nature of LPs, only very few papers consider the *indirect* effects of shocks generally, and even fewer consider the indirect effects of environment-related shocks, using local projections. Two notable exceptions are Ashizawa et al. (2022) and Roth Tran and Wilson (2020). Both estimate the indirect effects of natural disasters.[6] Ashizawa et al. (2022) investigate the indirect effects of disastrous floods in Japan on the real economy and examine various potential transmission channels of these indirect effects. They find that indirect effects matter in this context through three channels. First, across time: The negative impact of floods on GDP spills over to the year after the flood. Second, across sectors: Flood damage transmits across sectors depending on supply-side and demand-side factors relevant to the specific sector. Third, across facilities: Indirect effects are heterogeneous for different types of assets and facilities. Roth Tran and Wilson (2020) focus on the local impact of natural disasters in the US. While there are significant direct effects of such disasters affecting outcomes within a country in the longer run, an analysis of spatial spillovers finds

[6] Roth Tran and Wilson (2020) focus on direct effects but also analyze spatial spillovers.

that indirect effects propagating geographically in the longer term are close to zero.

Application to nature-related shocks

As reduced-form models, LPs by definition do not explicitly model a full dynamic system of variables in the economy (Jordà, 2005). This makes it harder, at first glance, to trace out indirect effects as they propagate. However, LP analyses can be readily applied to dependent variables that are only indirectly affected by a shock, or conducted separately across different regions or sectors (Jordà and Taylor, 2025). This allows researchers to let the data determine the relevant outcomes for analysis — a particularly important feature in the context of nature-related shocks, where established theoretical frameworks on propagation mechanisms are limited.

The capacity to apply LPs across diverse contexts and variables also provides a broader argument for the usefulness of the LP method for assessing the (indirect) effects of nature-related shocks on the economy. First, the approach can easily be adjusted when new knowledge on nature-related shocks becomes available. This is particularly important given our constantly evolving understanding of the complex dynamics underlying ecosystem services and environmental degradation. Second, as reduced-form models, LPs are more robust to misspecification (compared to more structural models, see discussion in chapter 3.3 below), making LPs better suited to deal with parameter uncertainty, as is often the case in the context of nature-related processes where key mechanisms may not yet be fully understood. The possibility to easily incorporate non-linearities further strengthens the relevance of the local projection method in the context of nature-related shocks, given that non-linearities such as tipping points are often discussed for nature-related processes (Lenton et al., 2008). The adaptability to complex and evolving realities, hence, makes LPs a particularly valuable tool for analyzing nature-related shocks.

3.3 Structural Vector Autoregressive Models (SVARs)

Impacts of shocks on macroeconomic variables are frequently analysed using Structural Vector Autoregressive models (SVARs). These models have been widely employed to assess the effects of monetary policy shocks (Sims, 1980; Blanchard and Quah, 1989; Christiano et al., 1999; Uhlig, 2005; Gertler and Karadi, 2015; Arias et al., 2019), as well as the macroeconomic consequences of financial indicators and uncertainty shocks (Bloom, 2009; Alessandri and Mumtaz, 2017; Ozdagli and Weber, 2017; Born et al., 2020b). Generally, SVAR models are applicable for studying both high-frequency monetary policy shocks (Gurkaynak et al., 2005; Gertler and Karadi, 2015) and low-frequency disturbances, such as technology shocks (Dedola and Neri, 2007; Dieppe et al., 2021).

SVAR models are part of the broader class of vector autoregression (VAR) models introduced by Sims (1980), where each variable is modeled as a function of its own past values and those of other variables in the system. This approach implicitly assumes that the system (typically an economy) consists of interrelated components whose historical interactions govern their evolution. However, while VAR models capture these dynamic relationships, the connections among variables are largely data driven and may not reflect meaningful economic relationships. SVAR models address this issue by imposing theoretically motivated restrictions, embedding economic structure into the model, thus enhancing the interpretability and intuition behind variable interactions (Christiano et al., 1999; Kilian and Lütkepohl, 2017). Within this framework, a central focus is placed on identifying structural shocks, i.e., the unexpected innovations to the system, which can then be traced through the model to study their dynamic effects on economic variables.

In an SVAR setting, the structural model can be represented as follows:

$$\mathbf{X}_t = \mathbf{D}'\mathbf{X}_{t-1} + \mathbf{B}\boldsymbol{\epsilon}_t \tag{2}$$

where $\mathbf{X}_t$ is a vector of endogenous variables in time t. In any VAR model, a key assumption is that $\mathbf{X}$ matrix is covariance stationary (i.e., each observation has a constant mean, constant variance, and constant autocovariance).

The matrices $\mathbf{D}$ and $\mathbf{B}$ impose the underlying structure of the system. ϵ is a vector of unobservable zero mean white noise processes, meaning its elements are serially uncorrelated and independent of each other. ϵ represents structural form residuals that have well-defined economic interpretations. This interpretation is provided by imposing identifying restrictions based on economic theory or external information (Uhlig, 2005; Ramey, 2016). These restrictions, used to construct the $\mathbf{B}$ matrix, can be broadly classified as either recursive or non-recursive. Recursive methods, such as the Cholesky decomposition, impose a hierarchical ordering that restricts contemporaneous causality to a single direction by imposing a recursive ordering via a lower triangular decomposition of the covariance matrix (Sims, 1980; Christiano et al., 1999). Non-recursive approaches include sign restrictions that constrain impulse response signs based on economic theory or prior knowledge (Uhlig, 2005), as well as narrative methods that leverage historical events for identification (Ramey, 2016). The ultimate choice between different identification strategies depends on the specific research question and the available data.

SVAR cannot be estimated directly as the shocks are unobservable. However, imposing invertibility assumption on matrix $\mathbf{B}$, and using some basic matrix algebra, allows rewriting the model in its reduced form:

$$\mathbf{X}_t = \mathbf{D}X_{t-1} + \mathbf{e}_t \tag{3}$$

where $\mathbf{e}_t = \mathbf{B}\epsilon_t$. Implicitly, invertibility of k-dimensional square matrix $\mathbf{B}$ requires defining $k(k$-1$)/2$ restrictions. This guarantees a one-to-one mapping between reduced-form residuals and structural shocks. Empirically, structural shocks are identified as residuals from a reduced-form VAR, in which each endogenous variable is regressed on its own lags—and potentially on additional variables—without imposing structural assumptions (Kilian and

Lütkepohl, 2017). Unlike the structural shocks which are by defintiion orthogonal, the reduced-form residuals are correlated among each other.

Typically, this estimation is carried out using Ordinary Least Squares (OLS), although alternative methods such as maximum likelihood or Bayesian techniques may also be employed (Karlsson, 2013). The obtained coefficients quantify each variable's response to specific shocks, allowing for the impulse response functions (IRFs) to be derived, which trace the dynamic effects of structural shocks over time (Christiano et al., 2005).

Formally, the impulse response function (IRF) measures the effect of a one-unit structural shock ϵ_j on variable X_i at horizon h and can be expressed as a matrix $\Phi(h)$:

$$\mathrm{IRF}_{i,j}(h) = \Phi_{i,j}(h) = \frac{\partial X_{i,t+h}}{\partial \epsilon_{j,t}} \tag{4}$$

IRFs show how variables respond over time to structural shocks, capturing both immediate and lagged effects, and illustrating shock propagation and duration. Forecast error variance decomposition (FEVD) complements this by quantifying the share of the forecast error variance of each variable attributable to specific shocks across horizons, revealing the drivers of macroeconomic volatility (Sims, 1980; Christiano et al., 1999). This share can be written as:

$$\mathrm{FEVD}_{i,j}(h) = \frac{\mathrm{Var}(\mathrm{IRF}_{i,j}(h))}{\sum_{k=1}^{n} \mathrm{Var}(\mathrm{IRF}_{i,k}(h))} \tag{5}$$

FEVD results are often summarised in a variance decomposition matrix, highlighting systemicness (a variable's influence on others) and vulnerability (its sensitivity to others).[7] Together, IRFs and FEVD clarify the dynamic interdependence of variables and how exogenous shocks shape system behavior (Diebold and Yılmaz, 2014).

In addition to tracing dynamic effects and identifying key sources of volatility, SVAR models are also highly adaptable to different data structures. Originally designed for time

[7] Systemicness is measured by column-wise sums and vulnerability by row-wise sums.

series, they have been extended to panel and global contexts through Panel VAR (PVAR) (Canova and Ciccarelli, 2013) and Global VAR (GVAR) (Pesaran et al., 2004) frameworks, enabling the analysis of cross-unit and cross-country spillovers.[8] VAR frameworks have also evolved to accommodate various shock types, including through non-linear VAR (NVAR) models, which relax linearity assumptions to better capture complex and state-dependent dynamics (Hubrich and Teräsvirta, 2013; Kilian and Lütkepohl, 2017). Other advancements include models such as Threshold VAR (Balke, 2000; Tong, 2012) and Smooth Transition VAR (Lundbergh et al., 2003), which account for non-linearities and regime-switching behavior based on threshold values. In addition, instrumental variable (IV) VAR techniques utilise external instruments to address issues of endogeneity and omitted variable bias, particularly in contexts involving natural experiments or reverse causality (Stock and Watson, 2018). These refinements allow for the incorporation of simultaneous feedback and improve modelling of realistic economic interactions.

Nevertheless, there are few things to keep in mind when using this approach. Because VARs rely on their own lags for prediction, a key drawback is that misspecifying the data-generating process leads to compounding errors and greater bias (Ramey, 2016; Nakamura and Steinsson, 2018). As described in 3.2, to address this, Jordà (2005) proposed the local projection (LP) method, which is similar to direct forecasting and generally exhibits lower bias, though at the cost of reduced precision, i.e. higher variance at intermediate and long horizons (Li et al., 2024). In general, unless there is an overwhelmingly concern at getting bias as low as possible, SVARs remain optimal across all horizons (Ramey, 2016; Li et al., 2024). However, recent findings indicate that, under certain conditions—primarily a finite number of lags—VAR and LP yield identical impulse responses (Plagborg-Møller and Wolf, 2021). This finding shifted the perception of local projections and vector autoregressive models from

[8]PVAR captures interdependencies across panel units over time, while GVAR models allow analysis of international transmission channels, useful for studying global nature-related shocks and distinguishing between permanent and transitory effects.

being substitute to complementary econometric methods.[9] Simply put, the choice between both approaches comes down to a trade-off between robustness needs (favoring LPs given their robustness to misspecification) and efficiency needs (favoring VAR) (Li et al., 2024).

More recently, VAR methodologies have increasingly been applied to examine how environmental disturbances, climate shocks, and natural disasters propagate through economic systems (Kahn et al., 2021). Several studies use SVAR approaches to analyse the macroeconomic and distributional effects of carbon pricing and transition risk. Using carbon policy surprises Känzig (2023) applies an external IV-SVAR and shows that tighter carbon pricing increases energy prices, lowers emissions, and stimulates green innovation, while reducing aggregate activity and increasing inequality. Using this same methodological approach, Benmir and Roman (2022) find asymmetric consumption responses to carbon policy shocks, widening inequality. Extending the focus from carbon policy to climate-related news shocks identified with coexceedance filter, Meinerding et al. (2023) trace their indirect macro-financial spillovers with Bayesian VAR.

Beyond carbon pricing, VAR-based studies probe broader climate risks and natural disasters effects. Cevik and Jalles (2023) combine static and dynamic panels for 158 countries and using PVAR show that climate vulnerability widens inequality. Other than that, Baker et al. (2024) treat natural disasters as exogenous uncertainty shocks, and using panel-IV and VARs find that disaster-driven uncertainty indirectly cuts short-run growth.

A growing body of research focusses on weather shocks, using SVARs and GVARs to capture how localised climate variability propagates through economic systems. Bacchiocchi et al. (2024) develop a monthly subnational GVAR model for 50 U.S. states and find that severe weather disasters in individual states lead to sizable nationwide output losses, driven by interstate trade and production linkages. Similarly, Cevik and Gwon (2024) use a structural VAR in monthly data from six major economies to show that weather anomalies disrupt

[9] Differences between both methods persist in practice due to finite-sample issues.

global supply chains, leading to increased inflation pressures and heterogeneous impacts between countries. At a global scale, Ahmadi et al. (2025) apply a Bayesian GVAR to a 33-country panel and show that temperature and precipitation shocks reduce output, with the strongest effects in hotter, developing countries, but also notable medium-term losses in colder developed economies. Importantly, international trade emerges as a key transmission channel, spreading the effects of local shocks globally. Complementing these macro-level studies, Gallic and Vermandel (2020) integrate a VAR with a theoretical framework to explore the role of weather shocks in agricultural fluctuations. By constructing the weather index based on the indicators for soil moisture, Gallic and Vermandel (2020) find that weather shocks significantly drive agricultural output variance after a two-quarter lag, with effects growing over longer horizons, highlighting the delayed and cumulative nature of weather impacts. Likewise, Kim et al. (2022) incorporate a severe weather index into a VAR for the U.S. economy and find persistent negative effects on growth, employment, and price stability, as industrial production slows, unemployment rises, and inflation increases, capturing multiple indirect channels of impact.

Application to nature-related shocks

SVARs offer a powerful framework for tracing dynamic effects of nature-related shocks across sectors and countries. Early work such as Mendonça et al. (2012) demonstrates how SVARs can model internal ecological dynamics (e.g., land-use trade offs) in the Amazon. They highlight how shocks to one natural asset (like forest cover) cascade into other forms of natural capital (such as cropland). This logic could be extended to capture broader economic impacts of nature shocks, such as impact on agricultural output, prices, or employment in nature-dependent sectors.

Nature shocks can also be analyzed using an approach similar to that applied to carbon pricing shocks. In line with the approach used by Känzig (2023), policy changes that constrain the use of natural capital - such as the establishment of conservation areas, adjustments to annual allowable cuts, or moratoria on resource extraction - can serve as exogenous instruments to identify the distributional effects of nature shocks on income.

Similar to weather-related studies like Bacchiocchi et al. (2024) or Ahmadi et al. (2025), nature-related shocks shocks may have more localised or industry-specific origins but spill over through supply chains and trade. For example, the sudden collapse of pollinator communities or crop failure in one region may affect food prices and output across borders. A GVAR or regional PVAR structure can help map these cross-country or intersectoral spillovers. SVARs also allow for testing whether nature shocks amplify not only output losses but also volatility, analogous to the approach in Gallic and Vermandel (2020), who link weather shocks to rising variance in agricultural output. Forecast error variance decomposition (FEVD) and historical decompositions can be used to quantify the contribution of nature shocks to observed macroeconomic fluctuations.

Finally, the literature (see, e.g., Almeida et al. 2025) identifies a range of vulnerabilities and amplifiers of nature-related shocks, underscoring the need to capture the interactions among these factors. In this regard, recent studies such as Ma et al. (2025) provide a solid baseline by employing a connectedness framework. More specifically, authors use a network-based approach derived from SVAR that quantifies both static and dynamic spillovers to examine how global biodiversity attention (a proxy for biodiversity loss) and climate policy uncertainty (GCPU) affect the stock markets of the G7 and BRICS nations. This approach could be extended to other nature-related shocks, linking them with both environmental and economic vulnerabilities, to better understand their comprehensive economic impact.

3.4 Production network models

The final class of approaches we review is production network models (PNMs). Some of the most prominent literature on PNMs, such as Jones (2011), Acemoglu et al. (2012), and Acemoglu et al. (2017), demonstrate that the propagation of (idiosyncratic) shocks and distortions via input-output linkages can have potentially significant implications for macroeconomic volatility and economic growth. Much of the literature has focused on how these interlinkages serve as transmission channels, transforming idiosyncratic or sector-specific shocks into aggregate fluctuations (Acemoglu et al., 2012). As shown by Acemoglu et al. (2017), even small, localised disruptions can be amplified by the network structure, generating outsized macroeconomic consequences. These models highlight how production networks both transmit shocks and transform localised disturbances into economy-wide effects (Carvalho and Tahbaz-Salehi, 2019). The literature has also looked at the interaction between the structure of a production network and additional frictions, such as asymmetric information and real rigidities (Pellet and Tahbaz-Salehi, 2023).

From a theoretical perspective, PNMs represent the economy as a web of interconnected industries linked through input–output relationships, where the output of one entity serves as the input for others. Based on the foundational work of Leontief (1951) on the structure of the US economy and extended by the seminal contribution of Long and Plosser (1983), PNMs provide a framework to analyse how (micro)economic shocks propagate through supply chains and affect the broader economy. By accounting for key structural features of networks, PNMs effectively encode and measure interconnections among economic units. Some important features of a network involve characteristics such as density (the average number of connections per node), weighted outdegree distribution (as a measure of heterogeneity along the input-supply margin), centrality (measuring a node's importance or influence within a network, based on its connections and the connectedness of its neighbors) (Carvalho, 2014). Along with capturing interconnectedness, general equilibrium theory allows for the tracing of how localised disturbances scale up to system-wide effects.

A baseline model of production networks allows for a representation of input–output linkages between various sectors via a weighted directed graph on n vertices. Each vertex in this graph—which we refer to as the economy's production network—corresponds to a sector, with a directed edge with weight $a_{ij} > 0$ present from vertex j to vertex i if sector j is an input supplier of sector i. A crucial element in PNMs is a sector's Domar weight, which is defined as a sector's sales as a fraction of GDP. In any efficient economy, the impact on output of a total factor productivity (TFP) shock to sector i is equal to i's Domar weight up to a first-order approximation (Hulten (1978) theorem). More specifically, if z_i denotes the TFP shock to sector i, then

$$\frac{d\log(GDP)}{d\log(z_i)} = \lambda_i,$$

irrespective of the household's preferences and the firms' production technologies. That is, a sector's Domar weight is considered (under the conditions of Hulten's theorem [10]) a sufficient statistic for how TFP shocks to that sector impact GDP. Hulten's theorem implies that, at a first-order approximation, aggregate outcomes remain unaffected by the underlying microeconomic details as long as the equilibrium sales distribution is observed. In other words, the first-order aggregate effects do not depend on factors such as the shape of the production network, the microeconomic elasticities of substitution in production, the degree of returns to scale, or the extent to which inputs and factors can be reallocated.

Several studies have examined how different shock characteristics (such as size and complementarities) influence their propagation in production network models (PNMs). For instance, Caliendo et al. (2018) consider the interplay between production networks and the spatial structure of production. Dew-Becker (2022) investigates how economies respond to large-scale shocks within a non-linear production network, focusing on the concept of tail centrality - a metric that captures the impact of severe negative shocks to specific sectors. Notably, it shows that greater interconnectedness in systems with production complementarities can dampen the effects of small shocks but heighten vulnerability to larger ones. Tintelnot et al. (2018) develop a quantitative model integrating domestic production networks with

[10] Hulten's Theorem states that aggregate output responds to firm-level productivity changes in proportion to each firm's Domar weight (i.e., its gross output relative to GDP). This means that productivity shocks to larger or more central firms have a greater impact on the overall economy due to direct and network effects.

international trade. In their framework, firm-to-firm connections within a country can adjust endogenously in response to global trade shocks. Their findings reveal that such endogenous network restructuring helps mitigate the economic damage of major negative trade shocks, while at the same time amplifying the benefits from trade from substantial positive shocks.

In recent years, the literature on PNMs has evolved beyond the simplifying assumptions of Hulten's theorem, recognizing that Domar weights are not always sufficient to fully capture the macroeconomic impact of a shock. Even when two sectors share the same Domar weight, the aggregate effects of a shock hitting each sector on the economy can differ. This is because Hulten's theorem offers only a first-order approximation of shock impacts (e.g., Baqaee and Farhi 2019), which can become inaccurate in the presence of large shocks due to non-linearities (Baqaee and Farhi, 2019). To address these second-order effects, researchers have explored more flexible production functions that allow Domar weights to adjust endogenously in response to shocks. By examining these second-order terms, it becomes possible to better understand the inherently non-linear dynamics of multi-sector models with production networks. Within this framework, Baqaee and Farhi (2019) use a calibrated multi-industry structural model featuring realistic production complementarities to assess how CES-induced non-linearities shape the propagation of shocks. In particular, they focus on how shocks affect factor shares and derive characterisations of the macroeconomic elasticities of substitution between factors and of the macroeconomic bias of technical change. Their findings show that these non-linearities amplify the effects of negative shocks when sectors are complements and amplify positive shocks when sectors are substitutes. This arises because the second-order derivative of aggregate output—i.e., the second-order term—is negative in the case of complements and positive for substitutes. Moreover, their analysis highlights that the scale of second-order effects is influenced by factors such as the elasticity of substitution.

PNMs have been applied to study the indirect economic effects of climate-related shocks and natural disasters, particularly by tracing how localised disruptions propagate through supply chains and amplify across sectors and borders.[11] In the context of natural disasters, Barrot and Sauvagnat (2016) show that when supplier firms are hit by disasters, their customer firms experience a drop in sales growth (and as already described in section 3.1). The authors validate their reduced-form findings using a general equilibrium production network model to predict reasonable magnitudes of the transmission of supplier disruptions within the production network. Similarly, Carvalho et al. (2021) use a calibrated general equilibrium PNM, in addition to the reduced-form analyses discussed in section 3.1, to estimate that network spillovers contributed to a 0.47 percentage point drop in Japan's GDP growth.

For climate transition risks, PNMs have been used to study how carbon pricing affects the economy through inter-sectoral linkages. Devulder and Lisack (2020) simulate a €100/ton carbon tax in France using a multi-sector general equilibrium model with input–output linkages. They find that costs from emission-intensive sectors propagate downstream via intermediate inputs, indirectly affecting less carbon-intensive industries. The model estimates a 1.2% GDP loss for France if implemented unilaterally (1.5% EU-wide), with value-added declines of up to 20% in sectors like chemicals and mining. Similarly, Frankovic (2022) applies a multi-region PNM calibrated to the World Input–Output Database to simulate global carbon pricing scenarios. The study finds significant sectoral heterogeneity, with carbon-intensive industries incurring the highest losses and substantial international spillovers due to trade linkages, amplifying the total economic impact when carbon taxes are adopted across trading partners.

Application to nature-related shocks

Overall, the PNM literature highlights the macroeconomic relevance of localized, strongly non-linear interactions.[12] This feature is critical when analyzing cascading effects following a nature-related shock, since such shocks often induce non-linear, feedback-driven disruptions

[11] Often, these structural models are estimated in addition to reduced-form analyses.

[12] See also related research on nonlinear shock propagation in economic networks: Jovanovic (1987); Durlauf (1993); Ballester et al. (2006); Elliott et al. (2014); Acemoglu et al. (2015, 2016).

within production networks. Consequently, the inherent ability of PNMs to capture threshold effects and contagion makes them particularly well-suited for assessing the macroeconomic risks associated with nature-related disturbances.

To study how nature shocks propagate along the production networks and affect the broader economy, these shocks can be incorporated into a general equilibrium input-output network model. In this framework, the shocks are assumed to reduce the productivity of specific sectors, which in turn diminishes the availability of inputs for interconnected sectors throughout the production network. This approach can be particularly useful for studying disruptions in the supply of ecosystem services or the destruction of natural capital that are used as factors of production. For instance, the literature argues that more than half of global GDP being moderately or highly dependent on nature and its services (World Economic Forum and PricewaterhouseCoopers, 2020; World Economic Forum, 2020). However, empirical evidence on how exactly disruptions in ecosystem services affect the economy remains sparse.

To integrate nature shocks in a PNM, one approach is to assume that only one sector directly utilises natural inputs as a production factor, while all other sectors acquire the output of this nature-dependent sector as an intermediate input for which they pay a price. In this setup, natural inputs indirectly influence market prices and quantities when the nature-dependent sector sells its output. When a nature shock occurs, the productivity of the sector that relies on natural inputs declines, and the resulting impact on aggregate output reflects the change in total production due to this productivity shock. Moreover, as outlined in Baqaee and Farhi (2019), the overall effect is mediated by the structure of the production network—particularly, how other sectors depend on the outputs of the nature-reliant sector. This framework can be generalised to include additional sectors that convert natural inputs into intermediate goods, thereby demonstrating how exogenous fluctuations in ecosystem services can trigger macroeconomic instability by cascading through supply chains and amplifying productivity shocks across sectors.

Baqaee and Farhi (2019) also explore the implications of correlated shocks, which are particularly pertinent in the context of nature shocks as it allows for the consideration of shocks affecting climate and nature simultaneously, such as shocks simultaneously impacting multiple ecosystems or affecting several producers dependent on diverse nature-based inputs, such as ecosystem services. The authors demonstrate that the second-order effect of a shared shock across two sectors is not merely the sum of the individual second-order effects from each sector. Instead, interactions between the shocks introduce additional non-linearities, highlighting the complexity of their combined impact. In a more recent contribution, Baqaee and Rubbo (2022) provide a comprehensive overview of recent advances in developing a flexible theoretical framework designed to accommodate the growing availability of highly disaggregated microeconomic data. These new datasets, characterised by fine granularity and high frequency, make it possible to closely observe how shocks are transmitted, propagated, and amplified throughout the economy, offering valuable tools for calibrating and constraining models at a highly disaggregated level.

However, as discussed in Geerolf (2022), PNMs do not represent a silver bullet and should be used with careful consideration over the assumptions that one imposes (i.e. whether the links are strictly linear, if the model captures dynamic evolution of firms and economies, how are heterogeneity of firms accounted for etc.) and thus the limitations. Importantly, and as discussed in Baqaee and Rubbo (2022), novel and highly disaggregated datasets have recently become available that are particularly interesting in the context of PNMs. This is especially true when it comes to data on the type of nature-related shocks we consider in this review. For example, the World Bank created a database of habitat maps in 2022 and introduced its global biodiversity database in 2024 containing millions of geo-referenced species reports (Dasgupta et al., 2024). Such datasets are crucial for studying the propagation of nature-related shocks in general, and using production network models in particular as pointed out in Baqaee and Rubbo (2022).

4 Conclusion

In this paper, we survey some of the growing literature on analyzing and quantifying the propagation of shocks through the economy. In particular, we review four methodological approaches frequently used to investigate the indirect effects generated through economic shocks in the economy: firm-level supply chain analysis, local projections, structural vector autoregressive models and production network models.

We also outline potential extensions of these approaches to nature-related shocks, defined as the degradation of nature and other changes in the availability and quality of ecosystem services (e.g., biodiversity loss), and discuss the main challenges and ways forward in this context. In particular, we highlight that, while some of the existing approaches can be readily used, nature-specific shock characteristics might require new specification and identification strategies. For example, the location-specific character of nature loss combined with natural and economic data availability might limit the regions for which impacts can be estimated. Furthermore, identifying shocks associated with slow-moving processes such as nature degradation can pose additional difficulties. However, as discussed, alternative shock identification strategies can help overcome this challenge.

Importantly, our review makes clear that no single methodological approach is sufficient to fully capture the indirect effects of nature-related shocks. Micro-level analyses, such as supply chain analyses, provide granular insights into firm-level vulnerabilities but may overlook broader macroeconomic feedbacks like price adjustments or substitution effects. Conversely, macroeconometric approaches, such as SVARs, capture dynamic macro-level responses but abstract from firm-level heterogeneity and detailed network structures. Integrating micro- and macro-level perspectives and combining the strengths of different approaches, however, promises to provide a thorough understanding on how shocks propagate: supply chain analysis can identify vulnerable nodes, PNMs can model the economy-wide propagation, and LPs or SVARs can quantify the overall dynamic effects on aggregate outcomes such as output growth and prices.

Overall, by providing a comprehensive review on commonly used methodologies on the transmission of economic shocks and identifying opportunities and challenges in applying existing methods to nature-related contexts, this paper provides a foundation for future analyses of nature-related shocks and their likely significant economic consequences.

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