WORKING paper

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Seeds of Inflation: Macro Modelling of Nature-Related Risks through Agricultural Prices

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Abstract

This paper analyses the macroeconomic materiality of nature-related risks, both physical and transition, through the illustration of the agricultural sector. Our results show that temporary shocks to major crops due to disruptions to ecosystem services could raise food inflation by over 2 percentage points and headline inflation by 0.5 point, with most of the impact materializing over a one- to two-year horizon. Should such one-off events be repeated or intensified, they could generate more persistent inflationary pressures. Moreover, in France, disorderly and unanticipated implementation of restrictions on agriculture inputs could reduce GDP by 0.2% and raise relative prices of agriculture by up to 12% over the medium to long term. These results demonstrate that while nature degradation can increase inflation, a well-planned and coordinated transition would mitigate these effects more effectively than disorderly action or inaction. The paper also underscores key modelling gaps – such as limitations in capturing nonlinearities, feedback loops, and sectoral interdependencies – while supporting better integration of nature into macro-financial frameworks for central banks and regulators.

Keywords: Nature-Related Risks, Macroeconomic Modelling, Price Stability

JEL: Q57 ; E31 ; E37 ; C60 ; E50 ; Q18

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NON-TECHNICAL SUMMARY

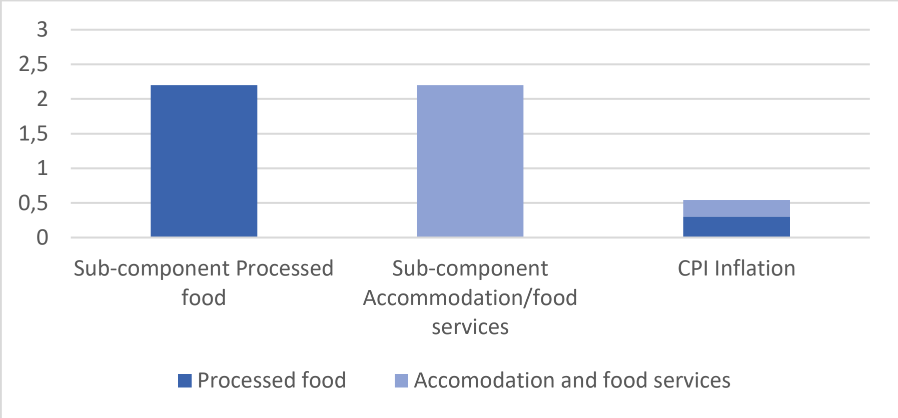
Nature provides economic activities with services whose economic value is often not reflected but which are nevertheless essential for production and, by extension, for price stability. Although ongoing environmental degradation threatens the continuity of these services and the economic activities that depend on them, these risks remain insufficiently understood and are rarely quantified in macroeconomic terms. This study examines how nature degradation and policies aimed at halting it can have tangible effects on the economy as a whole, using the agricultural sector as an illustration.

First, we design a case study of physical risks for the agricultural sector to show that disruptions to essential ecosystem services – such as pollination, pest control, invasive alien species and water regulation – can drive up food prices and ultimately affect headline inflation. Using a global value chain model, we simulate the consequences of natural hazards for agricultural productivity in a group of countries, as well as the impact on agriculture's relative prices for these countries, and in particular for France. Our results show that a shock affecting major crops could raise the relative prices of agriculture by 13% in France. We then use this temporary shock as an input in an inflation forecast model to assess the effects: we find that such physical risks could increase food price inflation in France by more than 2 percentage points and add around 0.5 percentage point to headline inflation, with most of the impact materializing over a one- to two-year horizon. Although these shocks are modelled as one-off events, repeated or intensified nature-related shocks could generate more persistent inflationary pressures.

In a second exercise, we model the impact of measures aimed at limiting pollution and reducing pressure on biodiversity. These policies are essential, but if they are implemented in a disorderly and unplanned manner, they can reduce agricultural production and lead to sharp price increases. In France, for example, disorderly implementation of strong restrictions on the use of pesticides and fertilisers could reduce GDP by around 0.2% and increase crop prices by 12% over the medium to long term. Similar effects are observed in other European countries, with particularly significant impacts in areas of intensive agriculture. These results should not be considered as *ex-ante* policy evaluation but as an illustration of the cost of insufficient anticipation of these policies. Besides, our results do not reflect the potential economic or health benefits associated with the transition of the European agricultural system.

Together, these two illustrative exercises demonstrate that while nature degradation can increase inflation, a well-planned and coordinated transition would mitigate these effects more effectively than disorderly action or inaction. This highlights that nature degradation is not just an environmental issue: it can lead to higher costs for households and businesses, and may pose challenges for monetary policy, particularly if such shocks become more frequent and persistent, with potential spillovers to other sectors and/or risks of de-anchoring inflation expectations. Our study also highlights gaps in existing modelling frameworks. Standard macroeconomic models often struggle to capture the complex interactions between nature and the economy, such as feedback loops, sectoral interdependencies, and non-linear effects that can amplify initial shocks. Better data, improved models, and further research are needed to systematically integrate nature into macro-financial risk assessments. Central banks have an important role to play in enhancing the representation of these risks and integrating them into policymaking.

Impacts of international nature-related agricultural productivity shocks on inflation in France



Inflation et risques liés à la nature : une approche macroéconomique par les prix agricoles

RÉSUMÉ

Ce document analyse l'importance macroéconomique des risques liés à la nature, tant physiques que de transition, à travers l'exemple du secteur agricole. Nos résultats montrent que des chocs temporaires subis par les principales cultures agricoles du fait de la dégradation de services écosystémiques pourraient faire augmenter l'inflation alimentaire de plus de 2 points de pourcentage et l'inflation globale de 0,5 point, la majeure partie de l'effet se matérialisant sur un horizon d'un à deux ans. Si ces chocs temporaires se répétaient et s'intensifiaient, ils pourraient générer des pressions plus persistantes sur l'inflation. De plus, en France, des restrictions désordonnées et non-anticipées sur l'usage des intrants agricoles pourraient réduire le PIB d'environ 0,2 % et augmenter les prix relatifs agricoles jusqu'à 12 % à moyen-long terme. Ces résultats montrent que, si la dégradation de la nature peut accentuer les pressions inflationnistes, une transition bien planifiée et coordonnée permettrait de mieux en atténuer les effets qu'une action désordonnée ou l'inaction. L'étude met également en évidence les limites importantes des modèles – telles que la représentation des non-linéarités, des boucles de rétroaction et des interdépendances sectorielles – tout en contribuant à une meilleure intégration des enjeux liés à la nature dans les cadres macro-financiers des banques centrales et des régulateurs.

Mots-clés : risques liés à la nature, modélisation macroéconomique, stabilité des prix

1. Introduction

Nature is generally defined as the entirety of the natural world, encompassing the diversity of living organisms and their interactions with the environment (IPBES, 2015). Beyond its intrinsic value, nature provides essential ecosystem services that underpin human activity. The rapid degradation of nature is documented in the scientific literature (IPBES, 2019), and central banks have started to explore its financial and macroeconomic consequences (NGFS & INSPIRE, 2022) (NGFS, 2023a). Five major direct drivers of pressure have been identified: land and sea use change, direct exploitation of organisms, climate change, pollution, and invasive alien species (IPBES , 2018a). The relationship between the economy and nature is bidirectional: economic activities both depend on nature and the ecosystem services it provides, and, at the same time, many of these activities exert adverse effects on nature, thereby threatening the stability of Earth systems and the uninterrupted provision of these ecosystem services. Nature-related economic risks can be divided into two categories: physical risks (linked to the degradation of ecosystem services) and transition risks (stemming from inadequate anticipation of public policies aimed at protecting or restoring nature). These risks can propagate through various transmission channels, at both microeconomic and macroeconomic levels.

An emerging body of literature seeks to characterize and quantify these nature-related economic risks (Dasgupta, (2021); NGFS (2023a); NGFS (2023b) ; Ranger, et al. (2023)). The assessment of physical risks is based on identifying economic dependencies on ecosystem services. Sectors such as construction, agriculture, and the agri-food industry are among the most exposed, as they rely on services such as pollination, which contributes to 75% of global food crop production. The lack of reference scenarios, reliable and harmonized data, and sufficiently granular models, both sectorally and geographically, complicates the assessment of the effects of nature degradation on macroeconomic aggregates, as well as the relation between local-level dependencies and those at the national or global level. As a result, prospective studies on the macroeconomic impacts of nature degradation remain scarce and typically focus on specific scenarios. For instance, Johnson et al. (2021) model the impact of the decline in ecosystem services such as pollination and timber provision on economic sectors compared to a baseline scenario, estimating that such damages could result in a loss of USD 90 to 225 billion in global real GDP by 2030, depending on the inclusion of carbon sequestration services. In a more severe scenario in which these ecosystem services collapse entirely, the GDP loss could reach USD 2.7 trillion by 2030 (i.e., -2.3% annually relative to the baseline).

In parallel with the literature on sectoral and economic dependencies on ecosystem services in the context of physical nature-related risks, the assessment of transition risks has initially focused on measuring the impacts of economic activities on nature, using these impacts as indicators of exposure to transition risks (Van Toor et al. (2020), Svartzman et al., (2021) and Calice et al. (2023), Boldrini, Ceglar et al. (2023)). The underlying assumption is that economic activities with significant negative impacts on nature are more likely to be affected by transition shocks aimed at halting biodiversity loss and ecosystem degradation – whether such shocks arise from regulatory measures, technological developments, or shifts in consumer or investor preferences.

While existing literature already provides a clear picture of the physical and transitional risks associated with the degradation of nature, there is still limited understanding of how these risks may translate into macroeconomic consequences and potentially jeopardize price stability. This knowledge gap is particularly relevant for central banks and supervisory authorities aiming to integrate nature-related risks into their macroeconomic assessments and policy frameworks.

To contribute to this emerging field, this paper presents a model-based analysis of the macroeconomic materiality of nature degradation, with a particular focus on the agricultural sector – a sector that is both highly reliant on ecosystem services and a significant contributor to environmental pressures. The primary objective of our analysis is to assess the extent to which nature-related risks could trigger inflationary episodes, particularly through sharp increases in agricultural prices.

Using a suite of macroeconomic models, we quantify the potential impacts of disruptions to key ecosystem services (physical risks) such as pollination, pest control and water regulation as well as the effects of tightening environmental regulations (transition risks) on food and consumer prices and broader macroeconomic variables. Our results suggest that shocks affecting major crops could result in substantial economic welfare losses for producers and sharp increases in agricultural prices. These price surges, transmitted through international trade and supply chains, could exert significant inflationary pressure. Treated as temporary shocks, our models show that they could potentially add up to more than 2 percentage points to food-related components of inflation and 0.5 percentage point to headline inflation, with most of the impact materializing over a one- to two-year horizon. As nature-related events grow in frequency and intensity, such shocks may become more recurrent, which may represent a rising challenge to price stability.

Similarly, transition shocks due to lack of policy anticipation can also give rise to significant macroeconomic consequences. We examine the effects of unanticipated and disorderly implementation of strong restrictions of the use of fertiliser and pesticides in the European Union. If insufficiently anticipated, changes in regulation can result in substantial losses in the value added of sectors targeted by the regulations, accompanied by sharp upward pressure on their prices. For France, our estimates indicate that a disorderly introduction of this policy could lead to a decline in GDP of around 0.2%, along with pronounced price increases: up to 12% for crops and plants, and around 5% for animal production over the medium to long term. Environmental regulations are necessary to mitigate environmental degradation and restore ecosystem services, but if implemented in a disorderly manner, such regulations can lead to significant macroeconomic disruptions and present risks to price stability. These results should not be interpreted as *ex-ante* policy evaluation but as an illustration of the cost of insufficient anticipation of these policies. If planned in advance and anticipated by economic agents[1], the consequences of the implementation of such restriction would be lower. Besides, our results do

[1] For instance, the "Farm to Fork" strategy in the European Union, after which our shocks were calibrated, was published in 2020, with objectives on fertilisers and pesticides set for 2030.

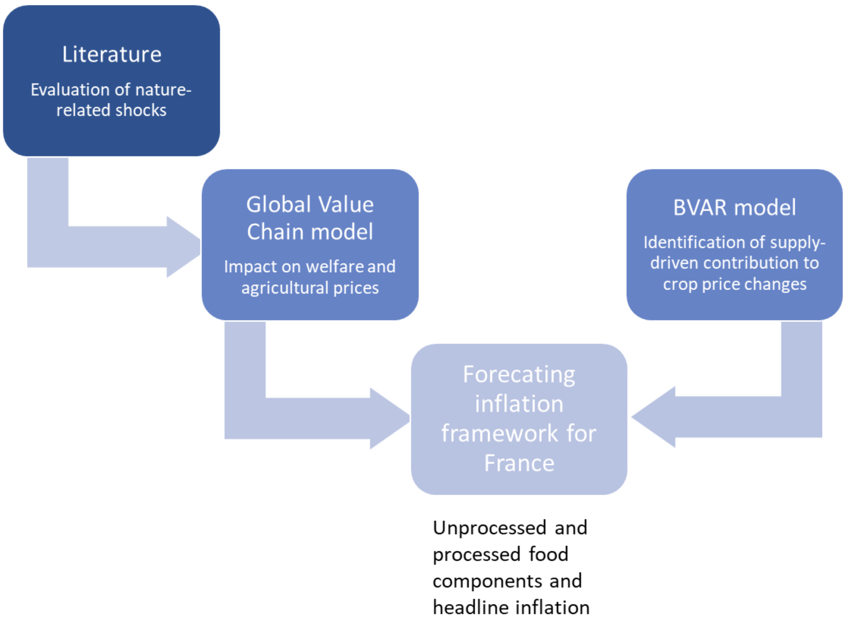
not reflect the potential economic or health benefits associated with the transition of the European agricultural system. Overall, well-designed environmental policies are necessary to address nature-related risks and restoring ecosystem services, on which economic resilience and well-being depend. To reduce uncertainty for firms and investors and support macroeconomic stability by minimizing potential unintended consequences, these policies must be implemented through clear, predictable, and harmonized public action.

The remainder of the paper is structured as follows: Section 2 focuses on the impact of physical risks and measures how shocks to large food commodity producers affect food prices and eventually French consumer price inflation. Section 3 presents the macroeconomic implications of asymmetric environmental policies implemented in a disorderly manner. Section 4 concludes with policy implications and recommendations for improving the integration of nature into macroeconomic and financial risk assessments.

2. Physical shocks and their transmission to consumer prices

This section examines how physical nature-related shocks, such as disruptions to agricultural production in key exporting countries, transmit through the global economy to affect food prices and headline inflation. To capture these dynamics, we rely on a multi-model approach. First, a global value chain (GVC) framework is used to trace the transmission of shocks across international production networks and quantify their impact on the prices of agri-food products. Second, a Bayesian Vector Autoregression (BVAR) model allows us to disentangle the relative contribution of physical shocks from other global drivers of inflation, while also identifying the structural channels at play. Finally, we complement this analysis with a semi-structural inflation forecasting model of French consumer prices, enabling us to quantify the inflationary effects of food commodity shocks identified previously. Figure 1 gives an overview of the methodology.

Figure 1: Overview of the methodological approach to assess the price impacts of physical risks



This integrated methodological approach provides a basis for assessing how environmental risks to agricultural production can propagate through global trade and supply chains, ultimately influencing domestic inflation dynamics.

2.1. Literature review of the economic impact of agriculture's nature dependencies

Among the various sectors of economic activity, the agricultural system shows a particularly high level of direct dependence on ecosystem services. First, agricultural activities rely on nature through the use of plant and animal species to produce biomass (organic matter of plant or animal origin) for both food and non-food purposes. Biodiversity is therefore essential to the structure, functioning, and processes of these systems, as well as to livelihoods, food security, and the provision of a wide range of ecosystem services (FAO, 2019). Agriculture also depends on nature in a broader sense, which includes not only biotic components such as biodiversity but also abiotic factors, notably the critical roles played by the hydrological cycle and soil structure in agricultural production. The ongoing degradation of ecosystem services critical to agricultural production (IPBES, 2019), largely driven by human –induced pressures on nature, poses growing risks to a sector that is heavily dependent on these services. Agricultural productivity, in particular, relies on four major ecosystem services that requires a particular evaluation: pollination, pest and disease regulation, invasive species control, and water related services. It is therefore crucial to assess the role of these services in supporting agriculture. Existing literature documents both the current state of decline of these services and the potential economic impacts associated with their disruption.

First, pollination is vital for the reproduction of 90% of wild plant species (IPBES, 2016) and supports 35% of global agricultural production, particularly fruit and vegetable crops (Klein, et al., 2006). Insects, and primarily bees, are the main providers of this ecosystem service. However, 16.5% of vertebrate pollinators are currently threatened with extinction (IPBES, 2016). The loss of pollinators could jeopardize between USD 235 and 577 billion in agricultural output (IPBES, 2019) , a risk exacerbated by the fact that (IPBES, 2019) estimates that the volume of agricultural production dependent on pollinators has increased by 300% over the last 50 years, due in particular to the increase in demand for agricultural products from crops dependent on animal pollination (such as cocoa beans, avocado, certain nuts and certain fruits). (Bauer & Sue Wing, 2016) estimate the share of the value of agricultural production per region of the world at risk in the event of the disappearance of pollinators; in 11 of the 18 regions, fruit is the most vulnerable, with at least 30% of the value of production at risk in 8 regions (including a large part of Asia, North America and part of Europe), and 50% at risk in one region, namely sub-Saharan Africa. In North America, for example, the walnut sector is the most vulnerable because of the high production of almonds, a crop with a high market value and which is highly dependent on pollinators. In the absence of pollinators, agricultural output could decline by 12.5% in China, 5% in the United States, and 2.5% in France (Potts, et al., 2016).

Second, the regulation of pests and diseases is a key ecosystem service that supports agricultural resilience. Agricultural biodiversity contributes to this natural regulation through the action of predators, parasites, and microorganisms. Greater species diversity enhances this regulation, but pesticide use, habitat fragmentation, and climate change have weakened these natural controls. In the United States, pest regulation services save an estimated USD 13.6 billion annually, with USD 4.5 billion directly attributed to predatory insects (Losey & Vaughan, 2006). Yield losses due to pests range from 26% to 40% for key crops such as maize, rice, and potatoes (Oerke, 2006), reaching up to 50% in parts of Africa and Asia. Another study by Savary et al., (2019) confirms the magnitude of cereal yield losses due to pests and diseases; according to this study, losses average 21.5% for wheat, 30% for rice, 22.5% for maize, 17.2% for potatoes and 21.4% for soya. Similarly, there are regional disparities, due in particular to climatic conditions and the geographical distribution of certain pest species: sub-Saharan Africa, the Indo-Gangetic plain and China experience higher losses on average. Despite increased pesticide use, yields continue to decline, partly due to growing pest resistance and the destruction of natural biological control agents.

Invasive alien species, introduced by human activities, also pose a significant threat to biodiversity and local ecosystems. Their number is projected to increase by 36% by 2050 (Seebens, et al., 2021). For instance, the fall armyworm can cause yield losses of up to 45% in maize crops in India. Overall, the number of invasive alien species is increasing at rapid and unprecedented rates worldwide (IPBES, 2023). Invasive species cause considerable agricultural losses, to varying degrees: Paini et al., (2016) estimate that the main agricultural commodity-producing countries such as China, the United States, India and Brazil could bear the highest absolute costs associated with new biological invasions, while developing countries, and in particular sub-Saharan African countries, appear to be the most vulnerable to these costs relative to the country's GDP.

Finally, natural ecosystems also play a vital role in regulating water flows by capturing and redistributing water resources essential to agriculture. These services are increasingly disrupted by alterations in the water cycle, exacerbated by climate change (e.g., floods, droughts). Water is the main limiting factor for crop production in regions of the world where rainfall is insufficient to meet agricultural needs (Steduto et al., 2012). Rezaei et al., (2023) estimate that yield reductions linked to drought amount to around 20% for wheat, 40% for maize and 25% for rice. They rise to around 30% for wheat and maize in the case of crop waterlogging (Rezaei, et al., 2023). As well as affecting the volume of production for many crops, disruptions to the hydrological cycle can lead to changes in the value of agricultural products. Bucheli et al., (2024) estimate that in the case of wheat, pre-harvest rainfall anomalies can cause up to 40% loss of income per hectare due to a deterioration in product quality.

Most studies on these four types of issues focus on specific crop-country pairs, and are not embedded within general equilibrium frameworks. As a result, they do not account for second-round effects or potential contagion across sectors and countries. Moreover, the quantified impacts are typically limited to yield or productivity losses, without considering implication on prices.

To address these gaps, we adopt a two-pronged approach. First, we develop an application using a global value chain model in which we aggregate shocks calibrated from the studies cited above, in order to illustrate the possible consequences for the world's largest producers should the four main nature-related hazards were to materialise - individually or simultaneously. Second, to complement this structural modelling, we estimate Bayesian Vector Autoregression (BVAR) models to analyse the price dynamics of key food products following supply disruptions. We then use both approaches to quantify the resulting pressures on food price pressures and their pass-through to consumer price inflation, using a forecasting model for French inflation.

2.2. Transmission of nature-related hazards to economic variables: a structural modelling approach

In a first application, we explore the impact of nature degradation on agriculture sector, as well as its macroeconomic consequences. The objective is to assess the exposure of crops to nature-related hazards, measured by yield losses, and to model the resulting effects on economic variables such as household consumption and agricultural prices.

A sector's exposure is defined here as the aggregate exposure of the crops that constitute it (i.e., the exposure of the French agricultural sector is determined by the exposure of the crops grown in France). The objective is to identify and estimate the exposure of crops to nature-related hazards, expressed as yield reductions caused by these hazards (i.e., yields of French crops may decline due to nature-related hazards occurring within France). The resulting aggregate yield reduction at the sector level is treated as a productivity shock, which is then used to assess its macroeconomic effects (e.g., on aggregate consumption and agricultural prices) through a global value chain model that quantifies and analyses the international transmission of shocks across multiple countries and industries.

Agricultural productivity shocks are calculated by aggregating the exposures (i.e., yield losses due to hazards) of the various crops that make up a country's agricultural sector. In a first step, a selection of crops is made based on the most widely produced cereals, fruits, and vegetables globally, as well as strategic crops relevant to agri-food, textile, and industrial production. The selection includes both food crops (cocoa, coffee, sugarcane, wheat, maize, soybeans, rice, bananas, oranges, apples, potatoes) and non-food crops (cotton, rubber). In a second step, for each selected crop, the five largest producing countries by volume are identified using FAO production data for the year 2021 (FAO, 2024).

Hazard selection

The resulting set of country-crop pairs (e.g., maize production in Brazil), serves as the basis for assessing exposure to a selected range of nature-related hazards. These hazards are identified based on a 2019 FAO report on the role of biodiversity in food and agriculture (FAO, 2019), which outlines the ecosystem services essential to food and non-food production. These services include provisioning services (i.e., biomass production), regulating and supporting services (such as pollination, soil-related services, climate and air quality regulation, regulation of natural hazards, pest and disease control, water-related services, and habitat provision), and cultural services (i.e., non-material benefits such as recreation, tourism, or spiritual value). We consider that the degradation of any of these ecosystem services constitutes a risk to agricultural production. The analysis focuses specifically on regulating and supporting services, as these most directly affect agricultural production conditions. Among them, we select pollination, pest and disease regulation, and water-related services, as well as the specific case of invasive alien species, which have materially impacted harvests in several regions worldwide (IPBES, 2024).

These hazards include both acute events (e.g., pest and disease outbreaks, or water cycle disruptions such as floods and droughts) and chronic pressures (e.g., pollinator decline). The inclusion of both temporalities is made possible by the medium- to long-term perspective of the model we use, which allows for both the frequent occurrence of acute hazards and the advanced progression of chronic ones.

A literature review is conducted to estimate the yield losses associated with each country-crop-hazard triplet (e.g., maize production in Brazil affected by invasive alien species). For instance, for pest and pathogens, we use an article providing ranges of yield losses for major crops in specific regions of the world, such as wheat, rice, maize, potato and soybeans. We take the lowest impact of the ranges provided for each region (Savary, et al., 2019). In addition, we use sources from the literature for specific crops such as cocoa (Guest et al., 2007), coffee (Cerda et al., 2017) and cane sugar (Li, et al., 2017). All these shock coefficients are based on observed data.

For invasive alien species (IAS), we use a report dedicated to IAS assessment (IPBES, 2023), as well as specific articles for some of the most relevant IAS (Early et al., 2018) which estimates projected impacts of wider invasions of the fall armyworm, Johnson et al. (2010), for pest of coffee based on observed data, and Pozebon et al., 2020, for soybean which projects impacts for soybeans culture in Brazil that we extrapolate to other soybean producers (USA, Argentina, China, India).

For water, we use recent work by Rezaei, et al., 2023 for wheat, rice and maize, together with a FAO report (Steduto et al., 2012) for soya, Najeeb et al., 2015 for cotton, Gateau-Rey et al., 2018 for cocoa, and Panigrahi et al., 2020, for bananas. All these shock coefficients are based on observed data.

Yield losses are expressed relative to a baseline scenario without hazards – that is, harvested output per unit of cultivated area is lower than under normal conditions. For these three hazards, estimates for a given triplet can be extrapolated to other countries for the same crop-hazard combination. For instance, yield loss estimates for maize in Brazil due to the degradation of pest and disease regulation services can be extrapolated to maize in Argentina under the same hazard.

An exception to this method applies to the pollination service: one study directly estimates the share of agricultural GDP lost per country in a projection of complete pollinator collapse (Potts, et al., 2016). This share is used as a proxy for the competitiveness shock affecting a country's entire agricultural sector, using the lower bound of the range provided in the paper. All studies used to estimate yield reductions for these four hazards are listed in the Appendix A, as well as a recap on their methodology (projected/observed) and on adaptation consideration.

For the majority of papers considered – specifically, all water-related risks as well as pests and pathogens – the literature provides observed historical shocks. In these cases, we project trend continuations, which precludes the issue of assigning ex-ante probabilities. In contrast, the pollination-related shocks used in our modelling are projected. The underlying study does not assign explicit probabilities to its scenario, which likely represents an upper-bound case, given it assumes a full collapse of pollinator populations. Shocks related to invasive alien species are mixed, as some papers are based on observed events and others represent the projected consequences of colonisation by given species – which is more likely to happen due to the intensification of global agricultural trade. As with pollination, both these hazards fall into the category of low-probability, high-impact risks, which justifies their inclusion in our framework.

Shocks by hazard

Productivity shocks are calculated at the country level for each nature-related hazard, by aggregating, for each country, the exposure of the crops that make up its agricultural sector to a given hazard. The shock coefficient c in country p for nature-related hazard $n \in$ {water, pollinators, pests and diseases, invasive alien species} is defined as follows:

$$c_{p,n} = \sum_i e_{p,n,i} \times S_{p,i}$$

with:

- $e_{p,n,i}$ exposure (expressed as a reduction in yields) of a crop i to hazard n in country p
- $S_{p,i} = \frac{production_{\,i,p}}{production_{\,p}}$ the share of production of crop i in the total production of the country's agricultural sector p

For example, the coefficient associated with the water hazard for Argentina[2] is:

$$c_{ARG,water} = e_{ARG,water,maize} \times S_{ARG,maize} + e_{ARG,water,soya} \times S_{ARG,soya}$$

Simultaneous Shock

The case of a simultaneous shock from all hazards is also analysed. It assumes the concurrent degradation of the three ecosystem services under study (pollination, pest and disease regulation, water-related services) and the increased prevalence of invasive alien species. Productivity shocks are then computed by aggregating the exposure of each crop, itself resulting from the aggregation of the crop's exposure to each individual hazard. The shock coefficient c in country p is defined as follows:

$$c_p = \sum_i E_{p,i} \times S_{p,i} = \sum i \left(1 - \prod_i (1 - e_{p,n,i})\right) \times S_{p,i}$$

With:

$E_{p,i}$ the exposure of crop i to all hazards n in country p

$e_{p,n,i}$ exposure of crop i to hazards n in country p

$S_{p,i} = \frac{production_{\,i,p}}{production_{\,p}}$ the share of production of crop i in the total production of the country's agricultural sector p

[2] Only two crops, soya and maize, are considered for Argentina according to the election method explained above.

For example, the shock coefficient for Argentina is:

$$c_{ARG} = E_{ARG,maize} \times S_{ARG,maize} + E_{ARG,soya} \times S_{ARG,soya}$$

With:

$$E_{ARG,maize} = (1 - 1(e_{ARG,water,maize}) \times (1 - e_{ARG,poll,maize}) \times \left(1 - e_{ARG,pests,maize}\right) \times \left(1 - e_{ARG,IAS,maize}\right))$$

Interpretation of productivity shocks

Based on shocks calibrated from the literature and applied to the relevant share of vulnerable cultures within each country's agricultural sector, we obtain the productivity shocks presented in the table below [Table 1]. These shocks are derived from the methodology described above and thus are not intended to support cross-country comparisons. These shocks result from a selective focus on specific countries, crops, and hazards, which does not allow for a comprehensive assessment of global agricultural exposure to nature-related risks, as discussed in Section 2.5.

Table 1: Productivity shocks in the agricultural sector

	Simultaneous shock	**Isolated hazard shock**			
Country	**Simultaneous hazards**	**Water**	**Pests and pathogens**	**Invasive alien species**	**Pollinators**
Argentina	0.377	0.213	0.156	0.089	0.100
Bangladesh	0.331	0.093	0.152	0.170	0.000
Brazil	0.488	0.080	0.266	0.231	0.025
Cameroon	0.007	0.006	0.002	0.000	0.025
China	0.346	0.085	0.120	0.118	0.125
Colombia	0.003	0.000	0.003	0.001	0.000
Ivory Coast	0.064	0.039	0.027	0.000	0.100
USA	0.432	0.245	0.176	0.072	0.050
France	0.115	0.055	0.069	0.000	0.025
India	0.373	0.059	0.205	0.167	0.025
Indonesia	0.171	0.052	0.076	0.077	0.025
Italy	0.044	0.000	0.000	0.035	0.100
Mexico	0.027	0.000	0.027	0.000	0.050
Nigeria	0.008	0.008	0.000	0.000	0.000
Pakistan	0.278	0.009	0.154	0.153	0.025
Poland	0.003	0.000	0.000	0.000	0.050
Peru	0.004	0.000	0.003	0.001	0.025
Russia	0.164	0.067	0.086	0.022	0.025
Thailand	0.207	0.000	0.127	0.113	0.000
Turkey	0.071	0.000	0.000	0.030	0.125
Ukraine	0.224	0.082	0.075	0.112	0.050
Viet Nam	0.232	0.061	0.108	0.113	0.025

Once the productivity shocks are calibrated, they are incorporated into a global value chain (GVC) model to analyse their international transmission across 65 countries and 45 sectors

(Serfaty & Stumpner, 2025[3]). This is a static multi-country, multi-sector general equilibrium model with input-output linkages, grounded in recent advances in international trade theory. Factor and goods prices are flexible, labor is supplied inelastically with no unemployment, and workers are mobile across sectors, making the model suitable for assessing the medium- to long-term effects of economic shocks. The model is "real," meaning it does not include money or nominal variables, and focuses exclusively on relative effects, such as changes in real wages, and can only compute relative prices (e.g., agricultural prices relative to other consumption prices). Calibrated using the OECD input-output table, the model estimates the impact of shocks on GDP and economic welfare (measured by real gross national expenditure) by country and sector. The model computes country-by-industry level productivity as an exogenous variable, while other relevant variables are endogenous: country-level wage, expenditure on final goods, sector employment and gross output, price index of intermediate inputs, etc.

In each country, each sector exhibits perfect competition with constant returns to scale. The production function is:

$$Q_{jt} = Z_{jt} {L_{jt}}^{1-\sigma_{jt}} {M_{jt}}^{\sigma_{jt}}$$

where M_{jt} is an aggregate intermediate good that aggregates across sectors and within sectors across different varieties. The model inputs it as a nested CES

$$M_{jt} = \left(\sum_{i} a_{jst}^{\frac{1}{\epsilon_t}} M_{jst}^{\frac{\epsilon_t - 1}{\epsilon_t}} \right)^{\frac{\epsilon_t}{\epsilon_t - 1}}$$

$$M_{\{jst\}} = \left(\sum_{i} b_{ijst}^{\frac{1}{\rho_{st}}} M_{ijst}^{\frac{\rho_{st} - 1}{\rho_{st}}} \right)^{\frac{\rho_{st}}{\rho_{st} - 1}}$$

The firm takes all prices as given and chooses inputs to maximize profits. Demand for labor and for the aggregate intermediate input are:

$$w_j L_{jt} = (1 - \sigma_{jt}) Y_{jt}$$

$$P_{jt}^M M_{jt} = \sigma_{jt} Y_{jt}$$

Demand for the aggregate intermediate good from sector *s* is:

$$X_{jst}^M = \beta_{jst}^M X_{jt}^M \text{ with } \beta_{jst}^M = \left(\frac{P_{jt}^M}{P_{jst}^M} \right)^{\epsilon_t - 1}$$

[3] Forthcoming as Banque de France Working paper

And with $X_{jt}^{M} = \sigma_{jt} Y_{jt}$. Demand by firms in sector t of country j for the variety produced by firms of country i in sector s is then:

$$X_{ijst}^{M} = \pi_{ijst}^{M} X_{jst}^{M} \text{ with } \pi_{ijst}^{M} = b_{ijst} \left(\frac{P_{jst}^{M}}{p_{ijs}} \right)^{\epsilon_t - 1}$$

The price index for intermediate goods from sector s used by country j and sector t has the typical CES form:

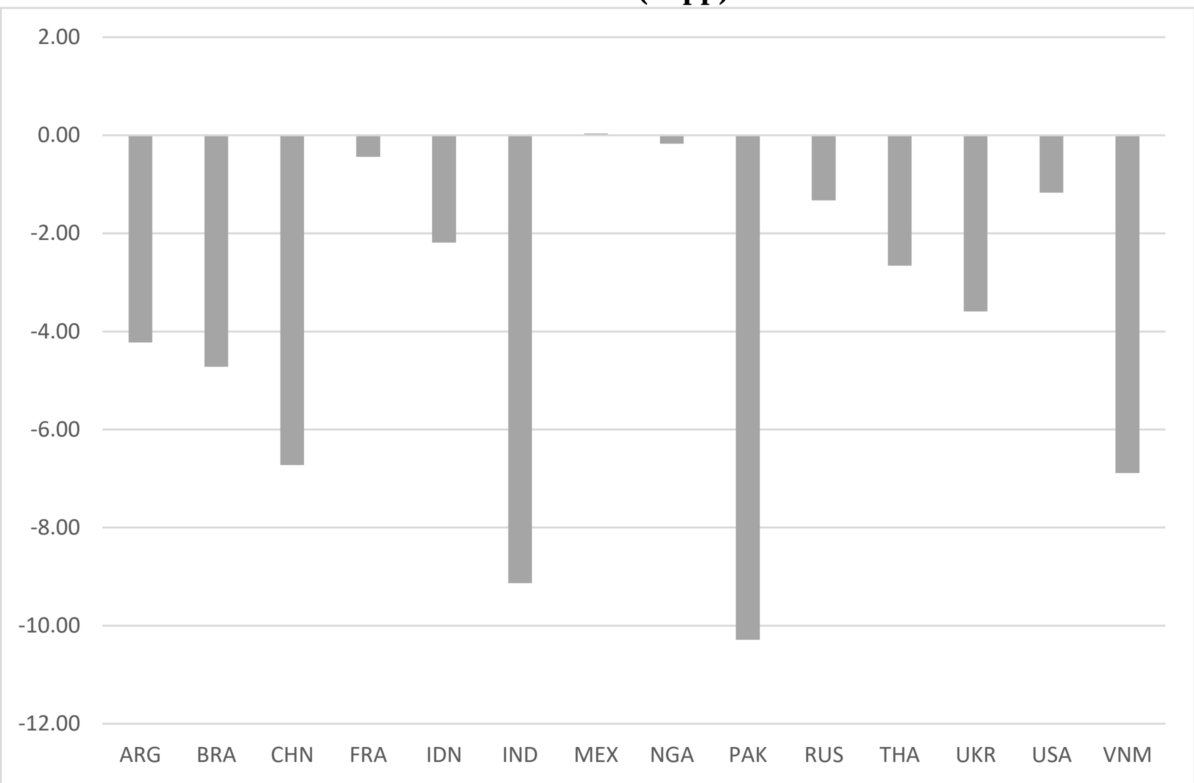
$$P_{jst}^{M} = \left(\sum_{i} b_{ijst} \, p_{ijs}^{1 - \rho_{st}} \right)^{\frac{1}{1 - \rho_{st}}}$$

and similarly for P_{jt}^{M}.

While these results should not be interpreted as forecasts and must be considered in light of the limitations discussed below, the estimated impacts of the previously calibrated shocks help illustrate the transmission channels through which nature-related risks can affect macroeconomic aggregates via existing intersectoral linkages. The charts below (Figure 2 and Figure 3) present the impact of the four nature-related hazards (cf. Table 1) on two economic indicators – welfare, and agricultural prices – for major agricultural producers. On the charts, the effects are represented in the case of a simultaneous occurrence of the four hazards.

While the highest productivity shocks were in Brazil (-0.49%) and the USA (-0.43%), the effects on these two countries are not among the highest of all the shocked countries, with -4.7pp on welfare in Brazil and only -1.2pp in the USA. Conversely, the countries most affected are Pakistan (-10.3pp), India (-9.13pp), Vietnam (-6.9pp) and China (-6.7pp), partly due to the weight of their agricultural sectors in the country's GDP. For all these countries, with the exception of China, the hazard with the greatest impact is ‘pests and pathogens’, which alone accounts for more than half of the total impact on welfare. For China, the contributions of the various hazards are relatively evenly distributed. In the case of France, the effects on welfare are mainly due to pests and pathogens (about -0.26pp alone) and water-related risks (about -0.21pp alone), out of a total impact of -0.44pp. The strong impact of the pests and pathogens hazard for most countries reflects the importance of these shocks in the calibrations described above, in line with the figures identified in the literature.

Figure 2: Impact of shocks linked to the four selected hazards on welfare for a selection of countries (in pp)



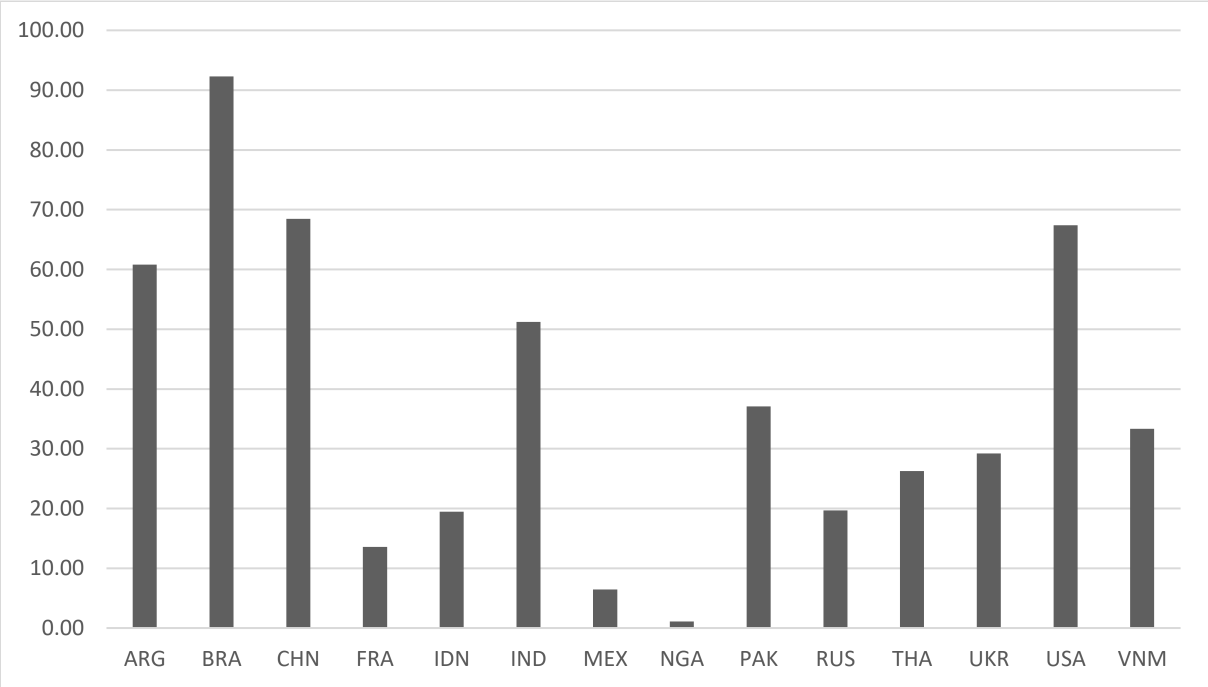
Note of interpretation: these results show the transmission of heterogeneous agriculture productivity shocks on welfare in affected countries. As the shocks are not calibrated as comprehensive scenarios for each countries (i.e. no probability, no adaptation, etc.), these results cannot be used as a standard comparison basis for between country impacts.

The effects on agricultural prices do not affect the exposed countries in the same way as welfare: here, the distribution of effects is closer to that of the calibration of productivity shocks on agricultural sectors. The countries most affected by agricultural price rises are Brazil (+92.3%), China (+68.5%) and the USA (+67.4%), as well as Argentina (+60.8%). However, in some cases, shocks of equivalent magnitude result in major differences in the sensitivity of agricultural prices. India, for example, experiences a shock similar to Argentina's (0.37 vs. 0.38), but the effects are smaller (+51.2% vs. +60.8%). The negative impact of welfare are shown without taking into consideration the potential mitigation effect of the terms of trade. Gouel and Laborde (2021) highlight that supply-side and trade adjustments can act as buffers against agricultural shocks. With comparable or stronger crop yield shocks due to climate change (e.g.an aggregate shock of -34.5% for all crops in Latin America), some countries have smaller impacts on welfare, or can see positive effects (e.g. +3.46% for Argentina). As demand is inelastic and large yield shocks induce price increases, countries that export a large proportion of their production are potentially favoured – or a minima less affected – than other countries. France is among these countries, with a +0.07% impact on welfare, compared to -0,44% in our simulations.

For most countries, the hazards with the highest contribution to price shocks are pests and pathogens (median contribution to total shocks of 0.41%), water (median contribution of

0.34%) then IAS (median contribution of 0.32%). This is the case for France, for which the majority of the total effect on prices (+13.6%) is essentially due to a +7.7% shock to prices caused by a pest and pathogen hazard taken in isolation, and a +6.1% shock caused by a water-related hazard taken in isolation. Depending on the type of crop grown in the country, the shock to pollination can be more or less significant. For example, it has an effect of less than +3% for a number of countries (Brazil, France, India, Indonesia, Nigeria, Pakistan, Russia, Thailand), but it significantly affects Argentina (+11.7%) and China (+17.5%).

Figure 3: Impact of shocks linked to the four selected hazards on agricultural prices for a selection of countries



Note of interpretation: these results show the transmission of heterogeneous agriculture productivity shocks on agriculture prices in affected countries. As the shocks are not calibrated as comprehensive scenarios for each countries (i.e. no probability, no adaptation, etc.), these results cannot be used as a standard comparison basis for between country impacts.

Our methodology applies the same treatment to chronic risks (pollination collapse) and acute risks (disruptions to the water cycle, invasive alien species, pests and pathogens). These shocks are aggregated in the ‘simultaneous hazards’ column, which gives the outputs of price variations that we use in the rest of our methodology to estimate the effects on inflation in France. As detailed in the discussion section, this overlooks the fact that chronic risks could be more persistent than acute risks which could materialise as one-offs shocks. However, we consider that this approach provides a meaningful illustration, in that environmental degradation leads to an increase in the frequency of these risks (extreme weather events, loss of ecosystem resilience), which could lead to a shift towards a regime in which these risks are more frequent and their effects more persistent, thus creating a trend that the GVC general equilibrium model is able to represent.

2.3. Identifying shocks to supply conditions and their impact on the major crop prices: A BVAR approach

The analysis of shocks related to climate and natural events on agricultural commodity prices reveals the materiality of their impact. Droughts and other environmental hazards affect agricultural prices, most often exerting upward pressure. In contrast to the previous bottom-up approach – which estimates the price impact of nature-related productivity losses based on literature for each crop and producing country – we also propose a top-down method that begins with the observed price movements of key agricultural commodities and infers the role of nature-related shocks using global macroeconomic data. Specifically, this approach analyses the variations in the prices of major agricultural commodities by breaking them down into three types of aggregated shocks: those related to global demand, those related to global supply, and those common to the commodities. The residual share, unexplained by these aggregated factors, is assumed to be idiosyncratic, that is, linked to local production conditions, primarily nature and weather-related risks.

To identify these four types of shocks (supply, demand, commodity and idiosyncratic shocks) we estimate Bayesian Vector Autoregressive (BVAR) including for each crop, its price quoted on world markets (yearly change), $p_{k,t}$, the aggregate price of commodity prices (yearly change), $\bar{p}_t$, a monthly indicator of world industrial production (yearly change), q_t, developed by Baumeister & Hamilton (2019), and a measure of world inflation, π_t, which corresponds to the median of annual inflation rate built from consumer price indices (seasonally adjusted) covering 143 countries developed by Ha, et al. (2023). These series cover the period January 1971- December 2023.

For each crop k, the model is written as:

$$B_0 y_{k,t} = \sum_{i=1}^{p} B_i y_{k,t-i} + w_{k,t}$$

where $y_{k,t} = \begin{pmatrix} q_t \\ \pi_t \\ \bar{p}_t \\ p_{k,t} \end{pmatrix}$ is the vector of endogenous variables of the model, w_t is a vector of structural shocks that are mutually independent, B_0 is the matrix of structural impact multiplier which describes the contemporaneous relationships among the model variables, B_i the coefficient matrix, and $p = 6$ the number of lags. The reduced form can be written as $u_t = B_0^{-1} w_t$, where

$$u_{k,t} = y_{k,t} - \sum_{i=1}^{p} A_i y_{k,t-i}$$

with $A_i = B_0^{-1} B_i$. Let's note $E(u_{k,t} u'_{k,t}) = \sum_{ii}$ the variance-covariance matrix of the reduced-form model. Hence, given the impact multiplier matrix, B_0, the reduced-form innovations can be represented as weighted averages of independent structural shocks, w_t . However, since the model is under-identified, additional restrictions are necessary to estimate B_0. To do this, we use an identification procedure bases on sign restrictions.

As specified above, the analysis identifies four types of shocks: a world demand shock, a world supply shock, an aggregate commodity price shock and an idiosyncratic shock. The latter is a shock that is specific to each crop under review and could be related to supply-driven disruptions, including nature and weather-related events. The identification procedure by sign restrictions is applied to the matrix B_0. The following restrictions are used:

$$u_{k,t} = \begin{bmatrix} + & + & - & \\ + & - & + & \\ + & + & + & \\ + & + & & + \end{bmatrix} \begin{pmatrix} u_{k,t}^D \\ u_{k,t}^S \\ u_{k,t}^C \\ u_{k,t}^N \end{pmatrix} = B_0^{-1} w_{k,t}$$

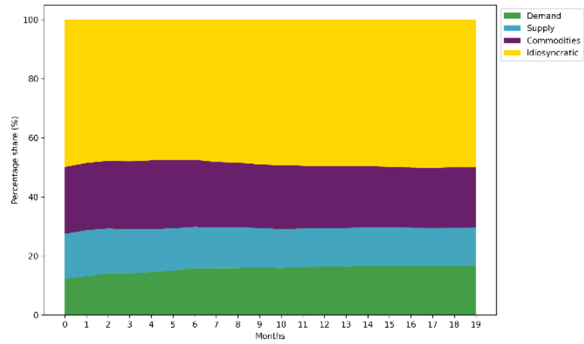
where the signs are imposed on the elements of the inverse of the impact multiplier matrix, B_0^{-1}, and all the shocks increase, by convention, the price of the agricultural crop considered. More specifically, a demand shock increases global industrial production, global inflation, the aggregate commodity price, and the price of product k (indicated by "+" signs in the first column of the matrix). The global supply shock has similar effects, except that it leads to a decline in global inflation (a "−" sign in the second column). The aggregate commodity shock reduces global production but leads to an increase in both the aggregate commodity price and global inflation, without necessarily affecting the price of product k. Finally, the idiosyncratic shock has no effect on global variables and only impacts the price of product k (last column of the matrix).

This analysis enables us to obtain several types of results. The forecast error variance decomposition (FEVD) shows the average contribution of each shock to the volatility of prices for each agricultural product. Figure 4 shows that fluctuations in agricultural commodity prices are mainly driven by idiosyncratic shocks (shown in yellow in the charts). These shocks account for between 35% and 60% of short-term price movements and around 40% in the long term (though only 25% for corn, which is an exception). Demand shocks explain between 10% and 20% of these fluctuations (up to 40% in the case of soybean oil), while global supply shocks generally account for a smaller share, except in a few cases such as rice or tea (20%). Aggregate commodity price shocks explain the remaining shares (between 10% and 20%).

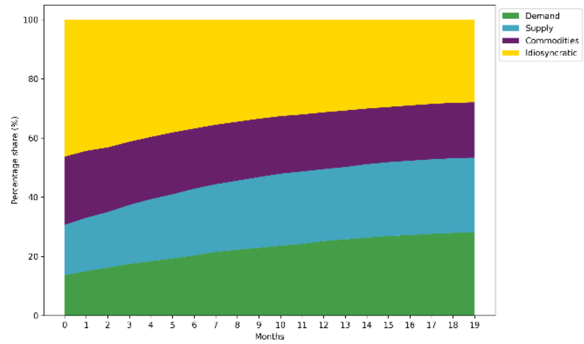
Figure 4: Breakdown of product price variances

Annual crops

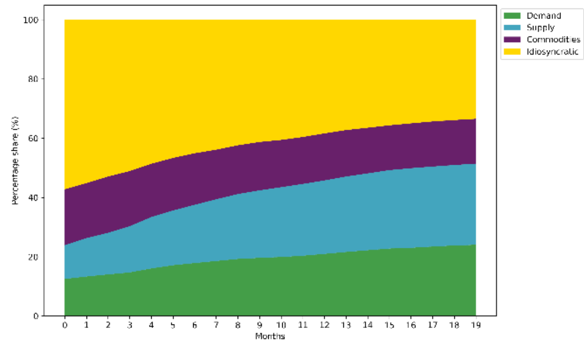
Cotton



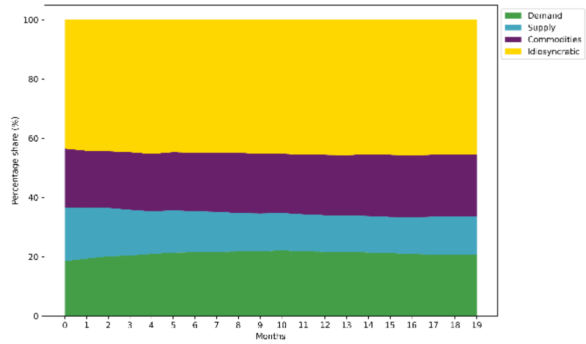
Maize



Rice

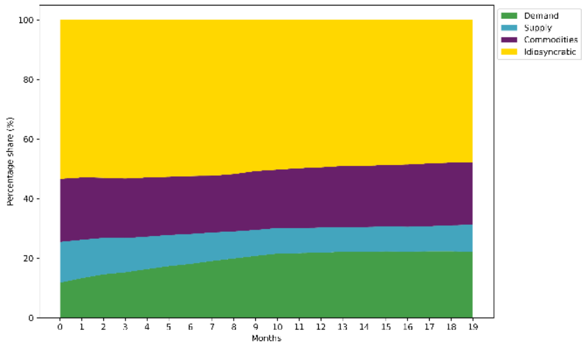


Soy meal

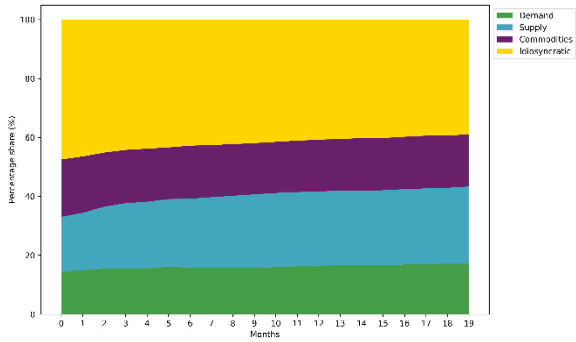


Perennials crops

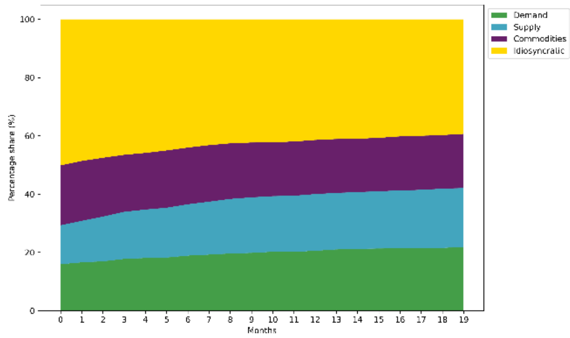
Cocoa



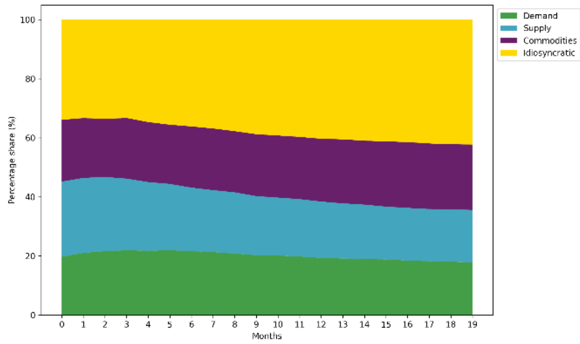
Arabica

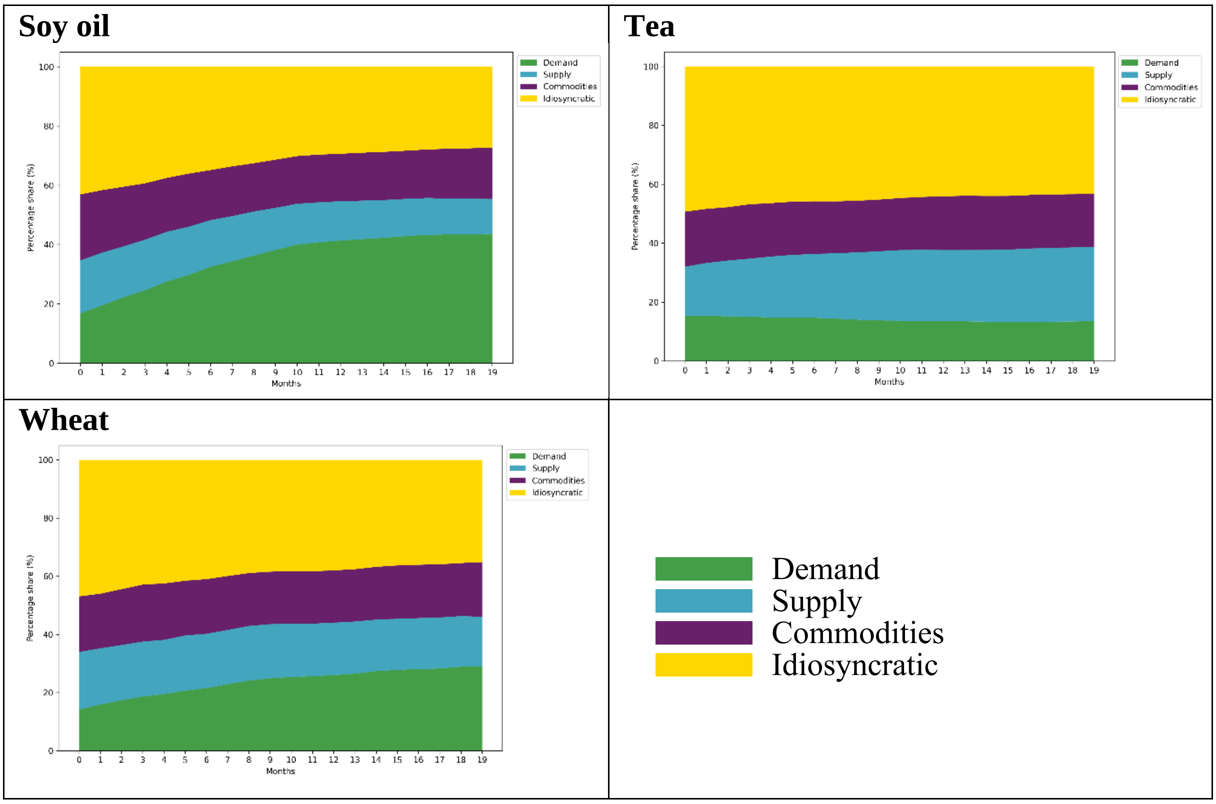


Robusta



Rubber





Historical decompositions allow us to identify episodes during which idiosyncratic shocks exerted upward pressure on agricultural commodity prices. Figures A1 and A2 (see Appendix B) show that the most significant increases in agricultural prices are often linked to idiosyncratic shocks, which are primarily due to weather conditions or the natural environment. These shocks can therefore be used as a quantification of the price effects of nature-related risks. Moreover, they can be associated with specific, well-known events – such as frosts or droughts – which to some extent validates the chosen methodological approach. For instance, the historical decomposition of Arabica coffee prices highlights the role of frosts in Brazil in 1976 or droughts in Brazil in 2015 and 2020, all of which are associated with an exceptional contribution from the idiosyncratic shock (yellow areas in the charts). Similarly, drought episodes in the United States (in 1996 and 2011) explain the surge in global corn prices. While these events are illustrative of the role of weather-related disruptions, they also underscore the broader importance of environmental shocks as a key driver of agricultural supply volatility. Although supply disruptions can stem from a range of factors – including input shortages, labour constraints, and trade measures – climate and environmental shocks account for the large majority of recent disruptions. For instance, FAO (2021) reported that between 2008–2018, disaster-related losses in crop and livestock production amounted to USD 280 billion, with 34% due to draughts, 20% to floods and 10% to crop pests, animal diseases and infestations. This predominance reinforces the relevance of using idiosyncratic shocks as a proxy for nature-related risks in the agricultural sector.,

The identification of idiosyncratic shocks is useful for assessing the magnitude of their contribution to price changes. Through a simple statistical analysis of these contributions (Table 2), we can determine their standard deviation and, more importantly, their maximum, in order to calibrate the shocks applied in inflation models (see 2.4). Risks related to production conditions therefore represent significant inflationary pressures: around a 10% increase year-on-year at one standard deviation, with maximum effects ranging between 30% and 40%. Even for commodities with the least volatile prices, such as corn, soybean oil, rubber, or tea, the maximum contributions still exceed a 20% year-on-year price increase.

Finally, while historical decompositions suggest that past episodes of agricultural commodity price spikes have been temporary, an increase in their frequency, driven by climate change and ecosystem degradation, could make such price pressures more persistent.

Table 2: Maximum Impacts of Idiosyncratic Shocks on Agricultural Price Variations (year-on-year)

Annual crops	*s.d.*	*Max*	Perennial crops	*s.d.*	*Max*
Cotton	10.7%	35.8 %	Cocoa	10.7%	35.8 %
Maize	7.6%	21.5 %	Arabica coffee	11.0%	44.1 %
Rice	11.4%	42.3 %	Robusta coffee	11.0%	38.4 %
Soya meal	9.6%	40.8 %	Natural rubber	9.0%	22.1 %
Soya oil	8.4%	24.7 %	Tea	7.2%	24.2 %
Wheat	8.7%	34.5 %			

2.4. Using a forecasting framework to assess the impact on French inflation

To assess the impact of the previously identified shocks on agricultural prices, we measure their effects on food prices and the hospitality/accommodation sector with Banque de France reference model of inflation forecasting, MAPI (Model for the Analysis and Projection of Inflation), extensively described in Ulgazi & Vertier (2022).

The MAPI model enables the forecasting of inflation in France over the short and medium term, with a time horizon of up to three years, using a bottom-up approach. It is based on a disaggregated method, analyzing 20 subcomponents of the Harmonized Index of Consumer Prices (HICP) over a 3-month horizon (referred to as the short-term horizon), and then 12 subcomponents from 3 months to 3 years. In the short term (3-month horizon), the MAPI model relies on analysis by forecasters and a few statistical models. Forecasters examine seasonal patterns in the 20 subcomponents to best predict the first three months (detailed specifications in Appendix C).

Beyond the short-term horizon (i.e., beyond three months), each subcomponent is modeled using specific models, either error correction models (ECM) or autoregressive equations (AR). Some subcomponents rely on macroeconomic explanatory variables such as wages, unemployment, import prices, or exchange rates, as well as assumptions provided by the ECB (e.g., oil prices, gas and electricity futures, farm-gate prices). This structure allows for the capture of specific price dynamics for each category while maintaining overall consistency.

We use MAPI[4] to measure the effects of shocks on agricultural commodity prices obtained from the two methodologies described in the precedent sub-sections: the general equilibrium

[4] The main equation developed to measure the impact of shocks on unprocessed food, involving the price of gas, wheat, etc., is not yet included in the MAPI framework but is the best candidate for the time being for this component. .

approach based on the GVC model (bottom-up) and the statistical approach based on the BVAR model (top-down).

It is important to note that the shocks in our analysis are assumed to occur instantaneously – that is, within a given month or quarter. This assumption aligns well with historical crop price behaviour. As shown in the historical decomposition of BVAR-based shocks (see Appendix B), price responses to shocks have typically been immediate in most cases. In contrast, the price effects derived from the GVC model should be interpreted differently: they reflect a shift from one general equilibrium state to another following a shock, which may unfold over a longer period. Some shocks, in fact, can be seen as gradual or slow-moving changes in production conditions. For this reason, while short-term inflationary effects might be overestimated, the long-term impact on price levels remains highly relevant and more realistic.

According to our simulations, however, the two approaches, that are not cumulative, give similar impacts on price levels and inflation. The idiosyncratic shocks on agricultural commodity prices, as derived by the BVAR model, could have an impact of around +0.4 percentage points on the total HICP, via its food component. Meanwhile, the GVC-based shock on agricultural prices would have an impact of approximately +0.5 percentage points on the total HICP, via its food and hospitality components. We detail here the methodology and underlying parameters used to derive such estimates.

Impact on HICP of shocks derived from BVAR models

To evaluate the impacts of idiosyncratic shocks on agricultural commodity prices, derived from the BVAR models, we develop an error correction modelling approach for the HICP of unprocessed food (3.3% of the total HICP basket in 2025). In the long-term specification, we include the futures prices of meat, wheat, and gas. We also add a dummy variable to account for the impact of Covid-19 on prices (lockdowns) and a time trend to include other long-term factors (such as the upward trend in labour costs). The specification is defined as such:

$$\Delta p_t^{unp} = c_{ct} + \alpha\big(\Delta p_{t-1}^{unp} - c_{lt} - \beta meat_{t-1} - \gamma gas_{t-1} - \delta wheat_{t-1} - \theta dummy_{Covid} - \mu * trend\big) + \pi\Delta p_{t-1}^{unp} + \sigma\Delta p_{t-2}^{unp} + \tau\Delta gas_t + \varepsilon_t$$

Table 3: Unprocessed Food HICP estimation results

Coefficients	Estimates
Long-term equation	
Error correction term (α)	-0.29***
Constant - short-term (c_{lt})	3.41***
meat prices (β)	0.10***
gas prices (γ)	0.03***
wheat prices (δ)	0.01*
dummy Covid (θ)	0.03***
trend (μ)	0.003***
Short-term dynamics	
Constant - short-term (c_{ct})	0.002**
Lagged dependent variable t-1 (π)	0.46***
Lagged dependent variable t-2 (σ)	-0.21**
change in gas prices (τ)	0.01***
R^2	0.38
Sample	2014M04-2023M12

*Notes: The table presents the econometric estimates of the unprocessed food HICP equation. The dependent variable is the change in unprocessed food HICP (Δp_t^{unp}). Estimates of the long-term equation parameters and short-term dynamics are detailed separately. */**/*** means significance level at 10, 5 and 1% respectively.*

We consider an idiosyncratic shock for the price of wheat (+34.5%), which directly translates into an impact of around +0.4% on the HICP for unprocessed food, resulting in a very limited impact of +0.01% on the total HICP. To indirectly estimate the impact of idiosyncratic shocks on the prices of maize (+21.5%) and soybeans (+40.8%), we use an auxiliary specification for meat prices (which appears in the equation for the HICP of unprocessed food). This results in a cumulative impact of +12% on meat prices, which then translates into an impact of +1.2% on the HICP for unprocessed food, ultimately leading to an impact of +0.04% on the total HICP.

In total, through the simultaneous materialisation of shocks on the prices of wheat, maize, and soybeans, we arrive at an impact of +1.6% on the HICP for unprocessed food, which corresponds to an impact of around +0.05% on the total HICP (see Table 5 and Figure 8).

To estimate the impact of idiosyncratic shocks on agricultural commodity prices on the HICP for processed food, we also opt for a more disaggregated approach, directly linking commodity prices to the sub-components of the HICP (e.g., the price of Arabica to the HICP for coffee). For this, we use an ARDL model, which is more flexible than error correction equations. Thus, the cumulative impact on the total HICP in the case of the simultaneous materialisation of all shocks would be around +0.36% in the long term. Table 4 below summarises the results of this approach.

Table 4: Summary of the impact of commodity shocks on the total HICP via sub-components of the HICP for processed food excluding tobacco

Raw material	**Shock size** (A)	**HICP variable of interest**	**Impact of the shock on the HICP variable** (B)	**Implicit elasticity of the final price to changes in the raw material** (C=B/A)	**Weight of the HICP variable in the total basket** (D)	**Impact on total HICP** (E=BxD)
Arabica	+44,1 %	Coffee	7,17	0.16	0.40 %	+0.03
Cocoa	+35,8 %	Chocolate	0,61	0.02	0.42 %	+0.00
Maize	+21,5 %	Alcoholic beverages	3,23	0.15	1,88 %	+0.06
Rice	+42,3 %	Rice	0,64	0.02	0.06 %	+0.00
Soya (beans)	+24,7 %	Other edible oils	15,04	0.61	0,07 %	+0.01
Tea	+24,2 %	Teas and infusions	1,99	0.08	0.06 %	+0.00
Wheat	+34,5 %	Bread and cereals excluding rice	7,98	0.23	3,09 %	+0.25
Total impact						**+0.36**

Impact on HICP of shocks derived from GVC model

In a second step, we seek to estimate the impact on inflation of the +13.6% shock to agricultural prices (measured at "farm gate" level), as derived from the GVC model presented in Section 2.2. To this end, we identify two transmission channels: processed food prices excluding tobacco, and prices in the accommodation and food services sector.

With regard to processed food prices, we first consider the specification currently used in our inflation forecasting model for France, which incorporates farm gate agricultural prices and *per capita* wages in the market sector. In order to account for the specific features of the recent period – marked by significant increases in agricultural prices linked to the post-Covid recovery and the outbreak of the war in Ukraine – we extend the estimation window of our equation (which, in its historical version, was estimated only up to Q4 2019). This results in a heightened sensitivity of processed food prices to agricultural prices. Under this specification, the agricultural price shock would translate into a +2.2 percentage point (pp) increase in processed food HICP excluding tobacco, and ultimately a +0.3 pp increase in headline HICP. The significance of these estimates is limited by the fact that they are based on a partial equilibrium approach and therefore excludes potential amplification effects of food price increases on other prices in the economy, as well as second-round effects on food prices themselves.

In addition, this effect would be compounded by the impact of the agricultural price shock (+13.6%) on final prices in the accommodation and food services sector (+0.2 pp). In an alternative partial equilibrium approach, we model prices in the accommodation and food services sector using an error correction specification that includes assumptions on agricultural prices, unit labour costs (ULC) in the relevant national accounts branch, and a dummy variable to account for measurement issues affecting ULCs during the Covid period.

According to this specification, a +13.6% shock to agricultural prices would, in forecast terms, result in a +2.2 pp increase in the HICP for accommodation and food services and, ultimately, a +0.24 pp increase in headline HICP over the long term (given a weight of 10.8% in the overall HICP basket in 2025).

Figure 5: Response of the HICP for processed food excluding tobacco to a shock of +13.6% in agricultural prices

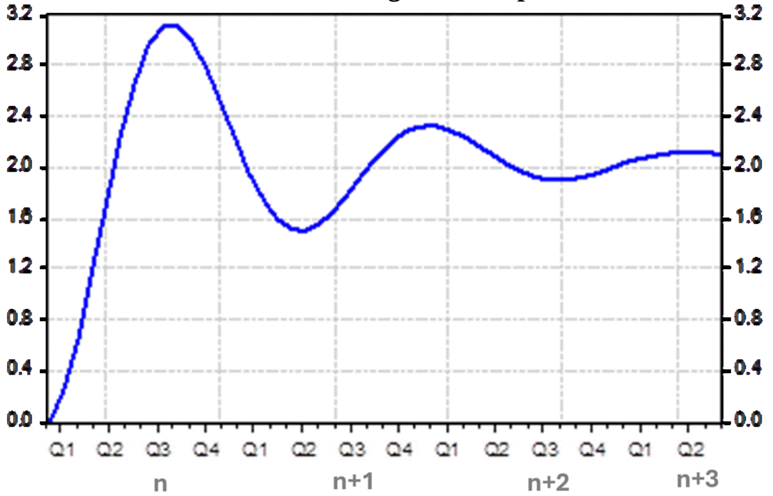


Figure 6: Meat price response to a 21.5% shock to the price of maize

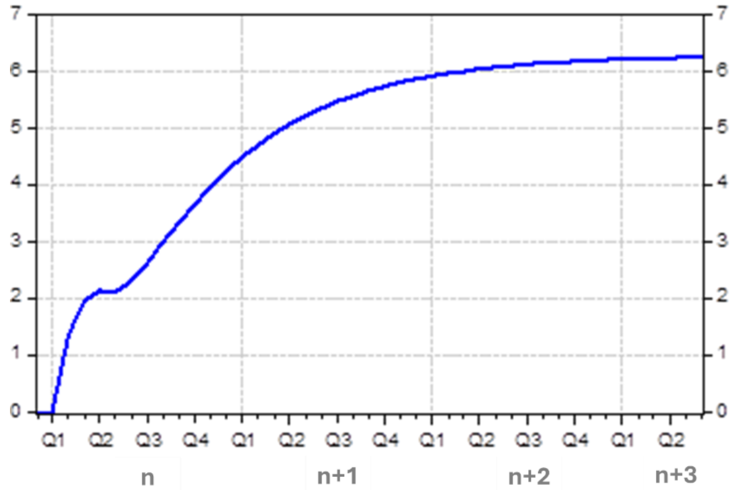
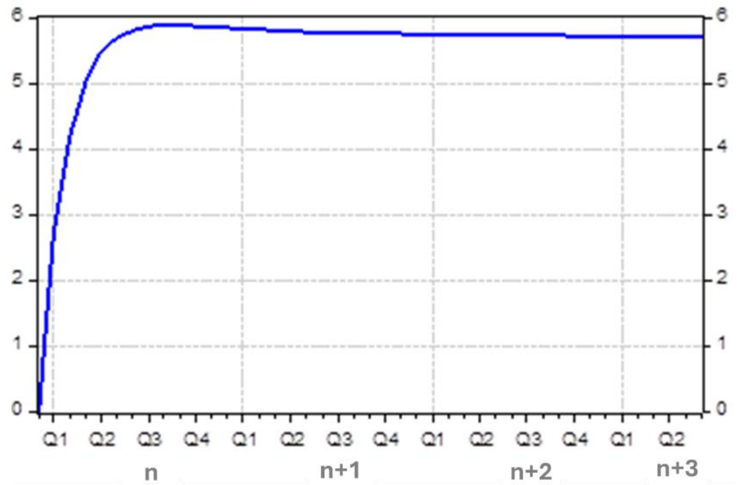


Figure 7: Meat price response to a 40.8% shock in the price of soya beans



The combined impact of the shock on headline HICP via the processed food component (+0.30 pp) and the accommodation and food services component (+0.24 pp) would thus result in a total effect of +0.54 pp on headline HICP, based on the shocks generated by the general equilibrium model (see Table 5 and Figure 9). The shocks we simulate are assumed to be one-off events, implying an immediate but short-term inflationary response, typically over a one-two year horizon. More precisely, the contribution of +0.30 percentage point from processed food inflation passes through quickly to overall inflation – within a few quarters –, while the impact from accommodation and food services inflation feeds through more gradually, over several years, as the hospitality sector adjusts its final prices more slowly. However, more frequent nature-related risks could result in recurring, and potentially more persistent, inflationary pressures.

Table 5: Estimated impacts of idiosyncratic and general equilibrium model shocks on France HICP

	Impact on HICP sub-components	Impact on total HICP
Idiosyncratic shocks (BVAR)	+1.6pp (unprocessed food)	+0.05pp
	+2.7pp (processed food)	+0.36pp
	Total effect of idiosyncratic shocks	**+0.41pp**
General equilibrium model shocks (GVC)	+2.2pp (processed food excluding tobacco)	+0.30pp
	+2.2pp (accommodation and food services)	+0.24pp
	Total effect of general equilibrium model shocks	**+0.54pp**

Note: *(1) The cumulative impact on headline HICP should be interpreted by type of shock, as the idiosyncratic shocks and those derived from the general equilibrium model stem from different methodologies and are therefore not additive; (2) Regarding idiosyncratic shocks, by summing the impacts on unprocessed and processed food, we assume that these effects are orthogonal. This assumption is credible insofar as shocks to commodity prices affect the processed and unprocessed components differently. However, a degree of overlap in certain effects, such as those related to wheat prices, cannot be entirely ruled out.*

Figure 8: Impacts on inflation in France in a BVAR modelling approach (pp)

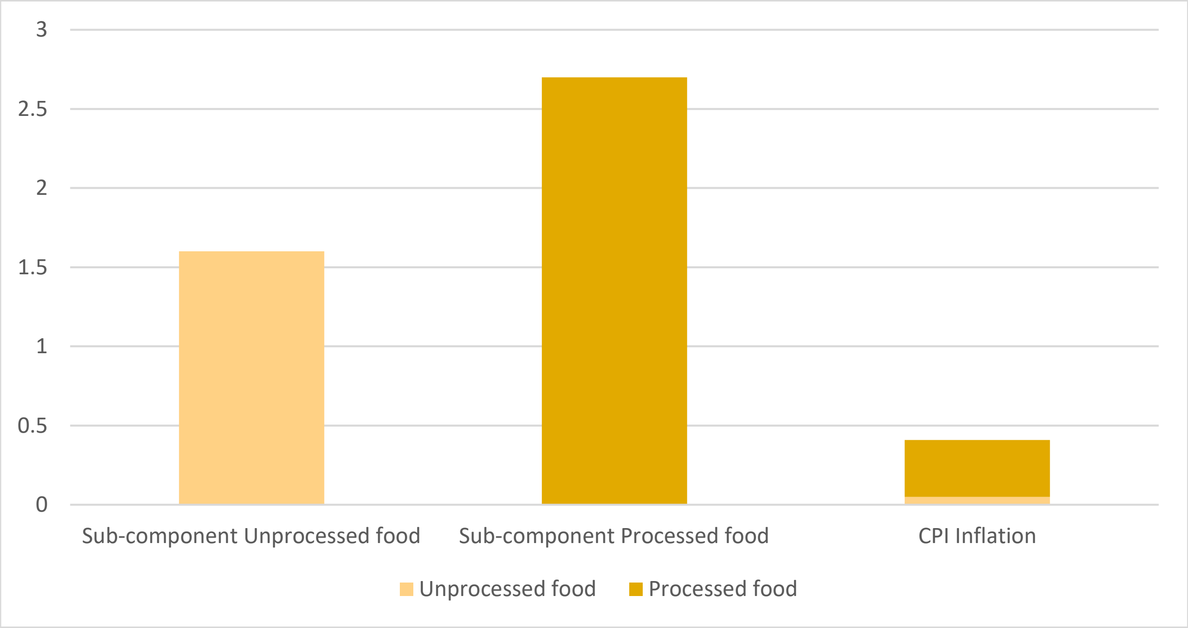
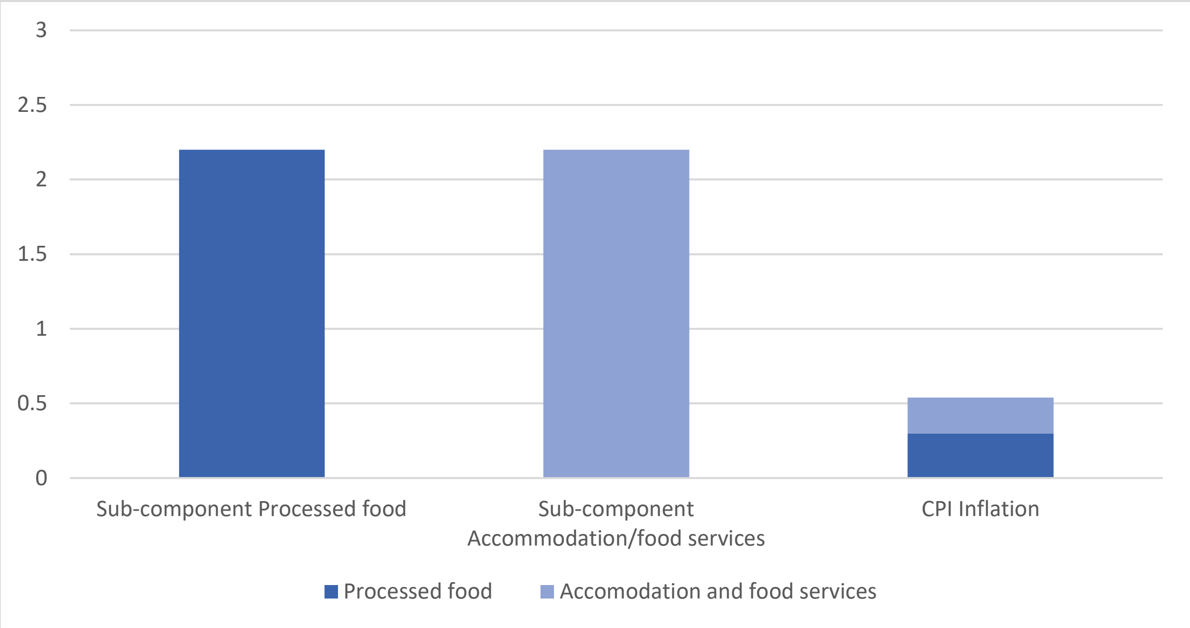


Figure 9: Impacts on inflation in France in a GVC modelling approach (pp)



2.5. Methodological considerations in the calibration and assessment of nature-related agricultural risks

The interpretation of the previous results in the bottom-up approach is limited by several aspects, some related to the calibration of the shocks, others related to their introduction in the models.

Limits related to shock selection and calibration

A first set of limitations is related to the methodology to derive the shocks, which relies on several assumptions and simplifications. First, the production data used to select the main producing countries for an agricultural commodity and to calculate the share of a commodity in the agricultural sector for a country are expressed in quantity (tonnes), and not in value. This method is independent of price fluctuations and therefore allows for a better comparison over time for a given commodity. However, it excludes the possibility to compare crops with each other, as their use or exchange value is not necessarily aligned with their physical quantity produced. As a result, this method can skew the perception of the importance of a crop in the total value added of the agricultural sector according to the value added intensity of a tonne.

Second, the analyses presented in this use case are partial in the sense that they only take into account a selection of countries, crops, hazards and studies estimating the effects of exposure to nature-related hazards. The choice of this selection, based on a sample of strategic crops and on the five main producer countries of these crops, omits crops and countries not included in this selection and yet likely to be exposed to nature-related hazards. Thus, the selection of crops by country should not be considered as a representation of a country's full exposure (see Appendix A), in particular as the literature available for the crops selected for a country may be limited. For example, Mexico is not covered by the risk linked to water because the only crop included in the Mexican agricultural sector is oranges, and we have only included literature on the exposure of oranges to pests and diseases.

Another possible limitation is that our selection may be biased towards crops with the highest commercial value rather than those most critical from a dietary perspective, given that we include commodities such as cocoa, coffee or orange in our sample. This potential bias is mitigated by the fact that we also includes staple cereals like maize and rice, which, although less commercially valuable per unit, are essential components of local diets and food security. The inclusion of high-value export crops reflects our specific interest in the transmission of yield shocks to market prices, as these commodities account for a significant share of traded agricultural revenues and thus have pronounced effects on income and external balances. We also consider this selection relevant for the assessment of the impact on French inflation given the significant weight of these crops in the food basket.

Besides, it is also possible that these hazards could materialise in smaller agricultural sectors, with disproportionate consequences for the local or regional economy. These effects are not captured in this use case.

Similarly, the selection of nature-related hazards provides a partial analysis of nature-related risks to agricultural production. There are other nature-related risks, in particular those linked to ecosystem services identified by the FAO (FAO, 2019), which are not included in this use case. In particular, soil-related ecosystem services are not considered, despite their fundamental role in agricultural production. Soil biodiversity is essential to certain soil processes such as decomposition, nutrient cycling, or protection against pathogens or erosion. However, restoring productivity on degraded soils is limited insofar as soils can be degraded to the point where they no longer respond to fertility improvement techniques (FAO, 2015). This characteristic implies non-linear effects of soil degradation on yields, which would amplify the magnitude of the shocks.

Another limitation relates to the methodology for calculating shocks, which is based on a study of the exposure of the various agricultural sectors to hazards linked to nature. This element is essential in the analysis of shocks and the interpretation of their results once they have been used as inputs in the model, as a comprehensive risk assessment should consider the existence of a hazard, the exposure to this hazard and the vulnerability to this hazard (Ranger, et al., 2023). In studying the exposure of each of the countries to the four natural hazards described above, we consider only one of the three aspects of risk, omitting the probability of the hazard and the potential adaptation of the agricultural sector of the countries concerned, which could reduce the severity of the shock. Part of the adaptation is dealt with in the model, given that agricultural goods, whether intermediate or final, can be substituted, irrespective of the type of crop and the geographical area.

Finally, the construction of the shocks linked to the scenario of the simultaneous occurrence of the four hazards raises uncertainties as to the magnitude of its consequences, which may be both overestimated and underestimated. On the one hand, the assumption of simultaneity could overestimate the magnitude of the shocks due to difficulties to estimate the probability that the selection of hazards occur precisely at the same time, particularly for one-off risks. On the other hand, this shock does not capture the potential chain reactions on agricultural production and other sectors. In particular, nature-related risks are subject to non-linear dynamics and potentially irreversible changes when tipping points are breached. Ecosystems are also deeply interconnected and interdependent (NGFS, 2023). As a result, the effects of the simultaneous emergence of risks may be disproportionately greater than the scale of the initial shock.

Limits related to shock simulations in the GVC model

A second set of limitations is related to the introduction of the calibrated shocks in the models. First, as discussed above, these shocks include both acute risks, which could manifest suddenly and with very short-term effects, and chronic risks, which involve permanent falls in productivity. In the GVC model we used, factor and goods prices are perfectly flexible, and workers are perfectly mobile between industries. For these reasons, the model is better suited to represent about medium-to-long run effects of economic shocks. We assume that these results are nonetheless of interest as acute shocks could occur more frequently, or even cause persistent damage, leading to long-lasting regime shifts corresponding to medium-to-long-run shocks.

Second, since the model used considers an aggregate agricultural good, it does not take into account the consequences of the occurrence of one or more hazards on a strategic agricultural good necessary to a particular sector (e.g. the reduction in rubber yields for the automotive sector, or cotton yields for the textile sector). The model does not represent the effects of the collapse of a specific type of agricultural good, which is non-substitutable and essential for other economic sectors.

From a broader perspective, a key limitation of treating the agricultural sector like other standard economic sector in our model lies in the distinctive features of both its demand and supply structures. On the demand side, agricultural products have highly inelastic final consumption, driven by minimum nutritional requirements and limited scope for substitution with non-food goods, although some substitutability exists within broad categories (such as starches or oils). This subsistence threshold represents the vital need for food consumption, in which perspective the elasticity of substitution in Hicks' sense is non-constant and, beyond the threshold, increases strictly and monotonically with the consumption of the subsistence good. In particular, the elasticity of substitution between the subsistence good and the others is 0 in the optimal allocation as long as income is too low to satisfy the level of subsistence consumption. Moreover, an increase in the price of the subsistence good requires a higher level of income to reach the subsistence threshold, which also transforms the substitutability relationship into a relationship of complementarity between goods (Baumgärtner et al., 2017). Such a hypothesis would then amplify the adverse consequences of agricultural productivity shocks on macroeconomic variables, since more resources would then be allocated to agriculture and aggregate consumption would fall in order to maintain the consumption of agricultural goods.

On the production side, agriculture relies on land as a specific and finite production factor, which is also critical for ecosystem services. Substitution possibilities between land and other inputs, such as fertilizers and pesticides, are limited and often entail different production technologies, as in the case of organic versus conventional farming. Moreover, agricultural inputs tend to exhibit low cross-price elasticities, unlike industrial inputs. In terms of trade, agricultural markets face comparatively high trade barriers, are tightly linked to energy markets (through biofuel production and fertilizer costs), and display heterogeneous levels of tradability across commodities, which affects the speed and extent of shock transmission and market adjustment. Together, these characteristics imply that standard modelling assumptions – such as smooth substitution, highly responsive supply, and frictionless trade – may systematically misrepresent the economic consequences of environmental shocks on the agricultural sector.

3. The macro-sectoral implications of disorderly transition policies

3.1. Macroeconomic impacts of environmental regulations in agriculture: Evidence from recent literature

Agricultural systems face the dual challenge of reconciling two often conflicting objectives: reducing environmental impacts while meeting the growing demand for food products. Europe provides a particularly illustrative example of this tension, given the scale of its agricultural sector and its significant contribution to environmental pressures. It is also at the forefront of using ambitious regulatory frameworks to drive the transition toward more sustainable agricultural practices. Indeed, while agriculture in Europe contributes significantly to environmental degradation, alternative production methods can enhance ecological resilience. Launched in 2019, the European Green Deal aims to reduce the environmental footprint of agriculture while ensuring food security and global competitiveness. It is structured around several key strategies, including the 'Farm to Fork' and 'Biodiversity 2030' initiatives. By 2030, targets include a 50% reduction in the use of chemical pesticides and nutrient losses, as well as a goal of dedicating 25% of agricultural land to organic farming. These measures seek to transform the food system in order to increase agriculture’s positive impacts, such as carbon sequestration and the preservation of natural habitats.

While an OECD study nuances the commonly held perception of environmental policies as economically detrimental (OECD, 2021), modest aggregate effects may conceal significant heterogeneity. Specifically, such policies may benefit low-emission and high-productivity firms by enhancing their productivity and export capacity, while adversely affecting more polluting and less efficient sectors. de L'Estoile & Salin (2024) illustrate how environmental policies can exacerbate the vulnerability of specific economic activities. For example, sectors such as agriculture and waste management in France appear particularly exposed to the “zero net land take” objective set for 2050. In contrast, other sectors, including wholesale and retail trade or manufacturing, may display greater adaptive capacity, despite their intensive land use.

The economic consequences of asymmetric environmental regulations are often discussed through the lenses of two main theoretical frameworks: the "pollution haven" hypothesis and the Porter hypothesis. According to the former, stringent regulations in one jurisdiction may lead firms to relocate polluting activities to regions with laxer environmental standards, resulting in pollution leakage. The Porter hypothesis, by contrast, assumes that stricter regulations may stimulate innovation and enhance competitiveness. Dechezleprêtre & Sato (2017) confirm that although the short-term effects of environmental policies on trade and investment are typically limited and contingent upon other economic determinants, they can be significant in specific sub-sectors where compliance costs are substantial. In such cases, competitiveness outcomes depend on the relative stringency of environmental regulation among competitors within the same market, thereby confirming pollution leakage effects aligned with the pollution haven hypothesis. Environmental regulation may, through cascading effects, influence a sector's competitiveness not only by affecting firms' economic performance, but also their technological choices and environmental outcomes. Similarly, (Bellora & Bourgeon, 2019) show that pesticide restrictions tend to be more stringent under free trade than under autarky, thereby reducing trade gains and increasing food price volatility.

Dechezleprêtre & Sato (2017) illustrate the cascading effects of stringent environmental regulations on firm competitiveness. First, regulations impose direct or indirect cost changes on firms. In response, firms adjust production volumes, pricing strategies, and investment behaviour, particularly in pollution-reducing technologies. These adaptations, in turn, affect economic outcomes such as profitability, employment, and market share. Third-order effects emerge in areas such as technological innovation (e.g., product or process innovations), international trade (e.g., trade flows and investment location), and environmental outcomes, including reduced pollution levels and mitigation of pollution leakage to other regions.

Several recent studies aim to assess the economic implications of the previously mentioned quantitative targets of the 'Farm to Fork' and 'Biodiversity 2030' strategies at the European and global levels. The studies agree on a reduction in agricultural production volumes, leading to an increase in food prices and then consumer prices in Europe and beyond, primarily due to the inelasticity of demand for agricultural products. The effects on other economic variables, such as agricultural incomes and food expenditures, vary:

- **Effects on production**: The reduction in the use of traditional agricultural inputs (pesticides, fertilisers, antimicrobials, land), which is beneficial for the environment, is associated with a decline in yields, resulting in a decrease in agricultural production across all studies (e.g. -5,2% on fruits and vegetables, -13,5% on beef meat and -11,6% on dairy according to Beckman et al., 2020). This is consistent with Bellora and Bureau (2016) who find that converting 20% of EU cropland to organic farming would reduce yields by 32% on average.
- **Effects on prices**: The effects on agricultural and food prices vary depending on the scenarios examined. Bremmer, et al., 2021 find that the decrease in supply within the EU leads to an increase in commodity prices, sometimes moderate (e.g., +3% for wheat), but more significant for other products (+33% for wine). This also consistent with Bellora and Bureau's scenario of 20% organic crop in the EU which leads to an increase of 1.5% to 3.5% in the global prices of the affected crops.
- **Implications for trade**: The decline in European production causes disruptions in trade. Bremmer et al. (2021) show that the EU would become a net importer of maize (+208.6%) and rapeseed (+98%), while reducing its net exports of wheat and wine (respectively -67% and -80% compared to the baseline). Barreiro et al. (2022) note a deterioration in the European agricultural trade balance, and Henning et al. (2021) estimate that the EU could become a net importer of wheat and beef, thus reversing its role as an exporter.

3.2 Assessing the macro-sectoral impact of disorderly transitions: an application with a sectoral model

In this application, we use the Banque de France's sectoral model (Devulder & Lisack, 2020) to simulate the effects of environmental regulations at the macro-sectoral level in the context of a globalised economy. Our quantification exercise focuses on a hypothetical scenario where unanticipated environmental regulation would be applied unilaterally by the European Union. We use the following hypothesis[5]:

- A 25% reduction in the use of fertilisers in the agricultural sectors;
- A 50% reduction in the use of chemical products excluding fertilisers (pesticides, antibiotics) in the agricultural sectors.

Tto reflect the disorderly nature of the transition, we assume that policy measures are implemented abruptly and without prior announcement. It is therefore not a policy evaluation of such measures, but rather an illustration of how a lack of preparation can amplify transition risks, with potentially negative macroeconomic and sectoral consequences, including threats to macroeconomic and price stability.

Model description

The Banque de France sectoral model is an amended version of the model developed by Devulder and Lisack (2020). The world economy consists of 9 countries/geographical zones and 84 sectors within each zone. The supply side is a sectoral production network where each sector produces from intermediate inputs (both foreign and domestic) and domestic labour. All inputs are substitutable to varying degrees, and companies operate in a perfectly competitive environment. In each country, a representative household supplies labour inelastically in a frictionless labour market and consumes domestic or imported goods. As all prices are flexible, the model cannot determine inflation and all prices must be understood as relative prices. The model is calibrated in line with the Exiobase3 database[6].

In each country $A \in C$ and sector $i \in \{1, \ldots, N\}$, a representative firm produces a quantity Q_{Ai} of good i from labour L_{Ai} and intermediate goods $\{Z_{Aji}\}$ (which correspond to energy goods if $j \leq N_E$ and to non-energy goods if $j \in (N_E, N]$ where N is the number of sectors per country[7]). Intermediate consumption of good j by sector i in country A is composed of good j produced locally, Z_{AAji}, and of good j sourced from all other countries $\{Z_{ABji}\}, B \neq A$ (these imported goods are grouped in the sub-aggregate Z_{AMji}). Each sector i produces using a technology represented by the following nested CES functions:

$$Q_{Ai} = \left(\mu_i^{\frac{1}{\theta}} L_{Ai}^{\frac{\theta-1}{\theta}} + \alpha_{AEi}^{\frac{1}{\theta}} E_{Ai}^{\frac{\theta-1}{\theta}} + \alpha_{AIi}^{\frac{1}{\theta}} I_{Ai}^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}$$

[5] Calibrated after the objectives for 2030 of Farm to Fork strategy, but frontloaded in the first year of simulation to illustrate the consequences of a disorderly transition.
[6] Exiobase - Home
[7] All countries produce all the varieties of goods.

$$E_{Ai} = \left(\sum_{j=1}^{N_E} \left(\frac{\alpha_{Aji}}{\alpha_{AEi}} \right)^{\frac{1}{\sigma}} \left(Z_{Aji} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

$$I_{Ai} = \left(\sum_{j=1+N_E}^{N} \left(\frac{\alpha_{Aji}}{\alpha_{AIi}} \right)^{\frac{1}{\epsilon}} \left(Z_{Aji} \right)^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}}$$

$$Z_{Aji} = \left(\left(\frac{\alpha_{AAji}}{\alpha_{Aji}} \right)^{\frac{1}{\eta_X}} Z_{AAji}^{\frac{\eta_X-1}{\eta_x}} + \left(\frac{\alpha_{AMji}}{\alpha_{Aji}} \right)^{\frac{1}{\eta_X}} Z_{AMji}^{\frac{\eta_X-1}{\eta_x}} \right)^{\frac{\eta_X}{\eta_X-1}}$$

$$Z_{AMji} = \left(\sum_{B \in C, C \neq A} \left(\frac{\alpha_{ABji}}{\alpha_{AMji}} \right)^{\frac{1}{\xi_X}} \left(Z_{ABji} \right)^{\frac{\xi_X-1}{\xi_X}} \right)^{\frac{\xi_X}{\xi_X-1}}$$

Where X=E si $j \leq N_E$, X=I si $j \in (N_E, N]$.

Company i in country A maximises its profit:

$$\pi_{Ai} = \max P_{Ai} Q_{Ai} - w_A L_{Ai} - \sum_{B \in C} \sum_{j=1}^{N} P_{Bj} (1 + \zeta_{ABji}) Z_{ABji}$$

Under constraint of its production technology. w_A is the wage rate in the country where the firm is located[8] and ζ_{ABji} is a tax on intermediate inputs from sector j in country B.

The representative household in each country maximises a CES utility function under budget constraints. The model assumes perfect international risk sharing: households trade bonds internationally, so that country-specific shocks affect household incomes abroad.

For simplicity, the government is not explicitly modelled. All tax revenues are assumed to be redistributed to households via lump-sum transfers.

Prices are assumed to adjust so as to guarantee simultaneous equilibrium in all markets.

Model calibration

The shares of inputs used for production in each sector (parameters μ, α), the relative sizes of the sectors and the shares of goods in final consumption are calibrated to match the data in the sectoral input-output and final consumption tables in the Exiobase3 database. The values of the elasticities of substitution (parameters $\theta, \sigma, \epsilon, \eta, \xi$) are taken from the literature and presented

[8] There is a single labour market in each country. Labour is perfectly mobile between sectors, but perfectly immobile internationally

in Appendix D (see Devulder & Lisack (2020) for a sensitivity analysis). We assume that the production technology is constant.

The measures are modelled as taxes on the consumption of targeted inputs (fertilisers, chemicals) by the targeted sectors (crops, livestock). These taxes are calibrated to induce a reduction in the use of the targeted inputs consistent with the reduction targets and tax revenues are fully redistributed to domestic households. It can be shown that, within this kind of model, such taxes have a strictly identical effect at the micro and macro levels to quantity targets.

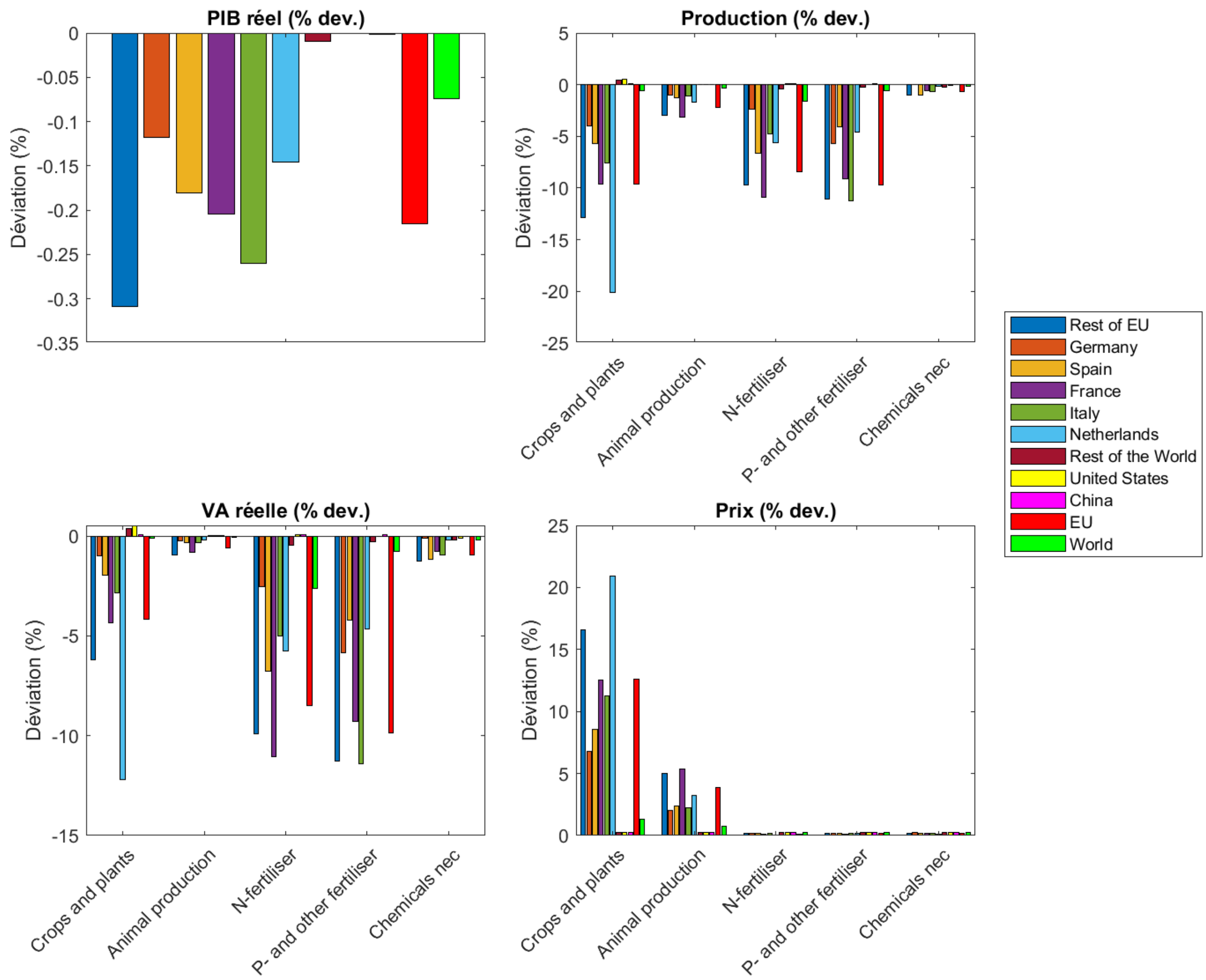
Main results

Although our model is not typically used for granular representations of environmental measures and the agricultural sector, we obtain an agricultural production shock consistent with the literature. It corresponds for instance with the 10-20% range of yield reductions estimated by Bremmer et al. (2021) based on case studies that also includes a measure to reduce nutrient losses by 50%.

Our simulation, in which EU countries only implement these disorderly environmental measures for the agricultural sector, would affect the competitiveness of the agricultural sectors of the countries concerned. The impact in absolute terms on GDP remains limited over the medium to long term (up to -0.27% for Italy, -0.23% for the EU, and -0.3% for the rest of the EU excluding the countries detailed on the graph), but the effects on production and prices in agricultural sectors are more significant. The unanticipated transition would also lead to a 10% drop in the production of crops and plants in the EU, and a drop of around 3% in livestock production. This aggregate effect masks heterogeneous effects between EU countries: Germany and Spain would be among the least affected (-4% and -6% respectively in crops and plants production, and -2% in animal production), while the Netherlands would suffer a -20% drop in production in the crops and plants sector. The effect on France would also be material, at around -10% in the crops and plants sector and -3% in livestock production. This hypothesis of policy implementation without level-playing-field corrective measures leads to a partial relocation of agricultural production outside the EU, thereby somewhat limiting the global effectiveness of the policy in reducing the use of targeted products.

The effects on relative prices would also be significant, with an increase of around 12% on crops and plants for the EU, and up to +21% for the Netherlands over the medium to long term. The effects would be material for most EU countries in this sector, with +12% for France, +11% for Italy, +8% for Spain, and +7% for Germany. At the global level, the effect would be limited to +2%, illustrating the risk to the competitiveness of the agricultural sector in European countries if this transition policy were not accompanied by measures to correct these effects. Overall, these results are consistent with the literature described above, as Bellora and Bureau (2016) found effects on global crop price between 1.5% and 3.5%, consistent with our 2% impact on global crops and plant prices. The effects would be less pronounced in the animal production sector, with around +4% for the EU, +6% for France, +4% for the Netherlands, and close to +3% for Spain, Germany and Italy over the medium to long term.

Figure 10: macro-sector impact, scenario of disorderly environmental policy in the EU



(*Source: BdF calculations)*

Agricultural sectors (crop and livestock production across regions) show highly heterogeneous exposure to the regulation, primarily driven by the current share of targeted inputs in the production process. A significant share of the regulation's impact on economic activity stems from indirect effects, as the shock propagates through non-targeted sectors via value chains. For example, a rise in the price of agricultural goods has a direct impact on the hotel and catering or agri-food sectors, which use them as inputs. Similarly, the effects in these sectors will then spread to other sectors upstream through demand for inputs or downstream through supply, and so on along the value chain.

These simulations do not take into account potential changes in household preferences or production technologies. They provide an order of magnitude for a limiting case. Additional measures – such as promoting the development of new production techniques, shifting consumer preferences towards organic farming, or ensuring similar rules for domestic and foreign agricultural products – could help limit the costs of the transition for European agriculture.

These simulations highlight the critical importance of anticipating and managing transition risks in the agricultural sector. Without accompanying measures, an abrupt and asymmetric transition could amplify sectoral vulnerabilities, erode competitiveness, and diminish the effectiveness of environmental goals at the global level. A more coordinated and gradual approach could help balance environmental ambitions with economic resilience. Moreover, the significant rise in food prices generated by this type of shock would directly feed into headline inflation, illustrating how transition risks in agriculture could also pose a threat to price stability through the food component of the consumer price index.

4. Discussion and way forward

This paper aims to shed light on the transmission channels through which nature-related shocks can affect price stability, both in countries directly exposed to these shocks and in their main trading partners. To do so, it presents two illustrative exercises: one focused on the physical risks linked to nature degradation – modelled through scenarios of extreme nature-related events affecting agricultural yields – and one centred on transition risks, in particular the impact of disorderly environmental policies. These two exercises are not meant to be directly compared; they are based on distinct modelling frameworks and assumptions, and they focus on different horizons. However, they both reveal that nature-related risks, if left unaddressed or poorly managed, can have inflationary effects. In the physical risk exercise, the impact on food prices is notable but contained in the short term, due to the transitory nature of the shocks. Yet, should these events become more frequent or severe, they could jeopardise price stability more durably. In contrast, the transition risk exercise highlights the effects of a disorderly policy path, showing that inadequate preparation and a lack of coordination can generate significant short-term inflationary pressures, especially in sectors such as agriculture. While the magnitude of price effects in the two exercises may appear comparable, their policy implications differ. Crucially, they underscore that a well-planned and coordinated transition – one that avoids abrupt shocks and includes supporting measures – would minimise inflationary risks and ensure a smoother adjustment. In short: an *orderly transition* is preferable to a *disorderly transition*, which is still better than a scenario of *no transition* and escalating physical damage.

While these case studies suggest that the overall impact on prices may not appear extreme, they are merely illustrative and subject to high uncertainty, and their interpretation must be nuanced by several considerations.

Firstly, most of the shocks represented here are one-offs, with limited persistence. However, if such risks were to intensify or succeed one another, they could threaten price stability by causing frequent and more persistent cost increases or create heightened financial tensions due to reduced profitability in exposed sectors.

Furthermore, this work focuses only on the agricultural sector, but the literature has shown that other sectors can also be very affected by physical risks linked to nature, due to the direct or indirect dependence of the activity of these sectors on the proper functioning of ecosystems.

For example, the construction sector could be very materially affected, as well as water-intensive industries, forestry, fishery and aquaculture, etc. (World Economic Forum, 2020).

This is also the case from the point of view of transition risk, by which the construction sector could be particularly affected, as well as sectors requiring a large amount of land for their activities (de L'Estoile & Salin, 2024). Similarly, while existing estimates anticipate moderate effects at an aggregate level in the case of an environmental transition policy, these results could mask much more pronounced sectoral impacts. For example, in the agricultural sector, transition policies could lead to direct or indirect cost changes for businesses. These businesses would react by adjusting their production volumes, product prices, and investments, particularly in pollution-reducing technologies. These adaptations could lead to reduced production, resulting in higher food prices and consumer prices in Europe and beyond, particularly due to the inelasticity of demand for agricultural products. As with climate-related risks, the short-term costs of transition policies may be high, but failing to implement them would result in much larger economic and environmental costs in the medium term. In that sense, Ranger et al. (2024) provide an illustration of a major health shock related to growing anti-microbial resistance caused by changes in land-use and deforestation globally, which would cause a combined effect of -12% GDP for the UK.

Finally, despite evaluating natural risks using our own models, our study also shows that current modelling tools remain insufficient to fully understand the impact of these risks. Standard macroeconomic models cannot yet capture all the complex dynamics specific to these risks, especially the interconnections between sectors, the feedback loops between the economy and ecosystems, and the non-linear effects of shocks on nature. The modelling applied to agriculture in this report is only a simplified illustration; to measure the potential effects of nature-related risks in their entirety, it would be essential to develop more sophisticated models capable of taking into account a multitude of factors and hazards. A NGFS report provides an initial assessment and a methodological framework for modelling nature-related risks (NGFS, 2023b). Improving existing methodologies so they account for all the key transmission mechanisms would allow for the design of scenarios and models better suited to nature-related risks.

Future research could expand this framework by incorporating a broader range of sectors and tailoring country-level scenarios according to the probability and materiality of nature-related risks, in line with the approach proposed by Ranger et al. (2024). Such granularity would allow for a more nuanced understanding of cross-country heterogeneity in exposure and vulnerability. In addition, assessing the financial transmission channels of nature-related shocks remains a critical area of enquiry, paving the way for the development of stress-testing methodologies that explicitly account for nature as a source of systemic risk. Finally, the integration of models that capture the frictions arising from the scarcity of specific agricultural commodities, such as rubber, cotton, or other inputs with key industrial uses, would enable a more realistic assessment of supply-side constraints and their macroeconomic repercussions.

Our findings also indicate that, although the primary threat to the economy from nature-related risks stems from physical shocks – whether occurring domestically or transmitted through international trade – the policy response plays a decisive role in the overall degree of macroeconomic impact. Environmental policies are a central factor in fighting the causes of ecosystem degradation and reducing the long-term risks associated with the loss of natural capital. However, if not carefully designed and introduced in a disorderly way, such policies may in turn generate significant short-term economic disruptions and exacerbate existing vulnerabilities. For this reason, the environmental transition requires a coordinated and well-planned approach, including early and clear policy signals as well as well-planned implementation timelines. Such an approach is essential to minimize economic disruptions, maintain public confidence, and ensure that environmental objectives are met in a stable manner.

Aligning environmental objectives across countries is also critical to reducing policy fragmentation and mitigating cross-border spillovers. Unilateral or uncoordinated measures can create distortions in trade and investment, leading to inefficiencies and competitiveness concerns, particularly in globally integrated sectors such as agriculture and manufacturing.

In sum, a successful transition depends not only on the ambition of the environmental objectives, but also on the coherence and credibility of the paths chosen to achieve them. Coordinated, stringent and well-anticipated policy frameworks are essential to find a way out of the paradox that the sectors most dependent on ecosystem services are also those causing their decline.

Appendices

Appendix A - Literature selected for shocks calibration in physical risks GVC modelling:

Pollination

- Potts et al., Safeguarding pollinators and their values to human well-being, 2016, Nature, doi:10.1038/nature20588

Pests and pathogens

- Guest et al., Black Pod: Diverse Pathogens with a Global Impact on Cocoa Yield, 2007, Phytopathology 97:1650-1653.
- Cerda et al., Primary and Secondary Yield Losses Caused by Pests and Diseases: Assessment and Modeling in Coffee, 2017, PLos One 12(1): e0169133. doi:10.1371/journal. pone.0169133
- Li, Loss of cane and sugar yield resulting from Ceratovacuna lanigera Zehntner damage in cane-growing regions in China, 2017, Bulletin of Entomological Research , 108(1):125-129. doi: 10.1017/S0007485317000608.
- NGhia, Titre de l'étude, 2021, Détails de la publication
- Savary et al., The global burden of pathogens and pests on major food crops, 2019, Nature ecology & evolution, https://doi.org/10.1038/s41559-018-0793-y
- Cotton Disease Loss Estimates from the United States — 2022, 2021, Crop protection Network, doi.org/10.31274/cpn-20230405-0
- Bassanezi, Yield loss caused by huanglongbing in different sweet orange cultivars in S˜ao Paulo, Brazil, 2017, Eur J Plant Pathol, 130:577–586 DOI 10.1007/s10658-011-9779-1

Invasive alien species

- IPBES, Summary for policymaker of the IPBES assessment report on invasive alien species and their control, 2023, IPBES secretariat, Bonn, Germany. doi.org/10.5281/zenodo.7430682
- Pozebon et al., Arthropod invasions versus soybean production in brazil: a review., 2020, Journal of economic entomology, 113(4), 2020, 1591–1608 doi: 10.1093/jee/toaa108

- Johnson et al., Coffee Berry Borer (Hypothenemus hampei), a Global Pest of Coffee: Perspectives from Historical and Recent Invasions, and Future Priorities, 2010, Insects, 11, 882; doi:10.3390/insects11120882

Water

- Gateau-Rey et al., Climate change could threaten cocoa production: Effects of 2015-16 El Niño-related drought on cocoa agroforests in Bahia, Brazil, 2018, PLoS ONE 13(7): e0200454. doi.org/10.1371/journal.pone.0200454
- Rezaei et al., Climate change impacts on crop yields, 2023, Nature Reviews Earth & Environment, https://doi.org/10.1038/s43017-023-00491-0
- FAO, Crop yield response to water, 2012, FAO Irrigation and drainage paper 66
- Najeeb et al., Consequences of waterlogging in cotton and opportunities for mitigation of yield losses, 2015, AoB PLANTS, 7: plv080; doi:10.1093/aobpla/plv080
- Panigrahi et al., Identifying opportunities to improve management of water stress in banana production, 2020, Scientia Horticulturae, https://doi.org/10.1016/j.scienta.2020.109735

Database for physical risk case study

- OECD. Oecd-fao agricultural outlook 2020-2029. https://www.oecd-ilibrary.org/sites/57d27093en/index.html?itemId=/content/component/57d27093-en, 2024. Accessed in June 24.
- Statista. World fruit production. https://www.statista.com/statistics/264001/worldwideproduction-of-fruit-by-variety/, 2024. Accessed in June 24.
- Statista. World vegetable production. https://www.statista.com/statistics/264065/globalproduction-of-vegetables-by-type/, 2024. Accessed in June 24.
- FAO. Cultures et produits animaux. Online database, 2024. Accessed in June 24

Hazards	Selected paper	Projected or observed event	Adaptation
Poll	Potts et al. 2016	Projected (no animal pollinators)	None
P&P	Guest et al. 2007	Observed	
P&P	Cerda et al. 2017	Observed (field exp.)	None
P&P	Li et al. 2017	Observed (field exp.)	None
P&P	Nghia 2021	Observed	
P&P	Savary et al. 2019	Observed	
P&P	Crop protection network	Observed	Probably (survey)
P&P	Bassanezi et al. 2017	Observed (field exp.)	Probably
IAS	IPBES + Early 2018	Projected	None
IAS	Pozebon et al. 2020	Projected	None
IAS	Johnson et al. 2010 WIRYADIPUTRA 2008	Observed Observed	Cited in WIRYADIPUTRA Not mentioned
Water	Gateau-Rey et al. 2018	Brazil: Observed Indonesia: Observed (field exp.)	Probably in short term
Water	Rezaei et al. 2023	Observed	
Water	FAO 2012	Observed	Not mentioned
Water	Najeeb et al. 2015 Wu et al. 2012	Observed Observed	Cited in Wu 2012 None

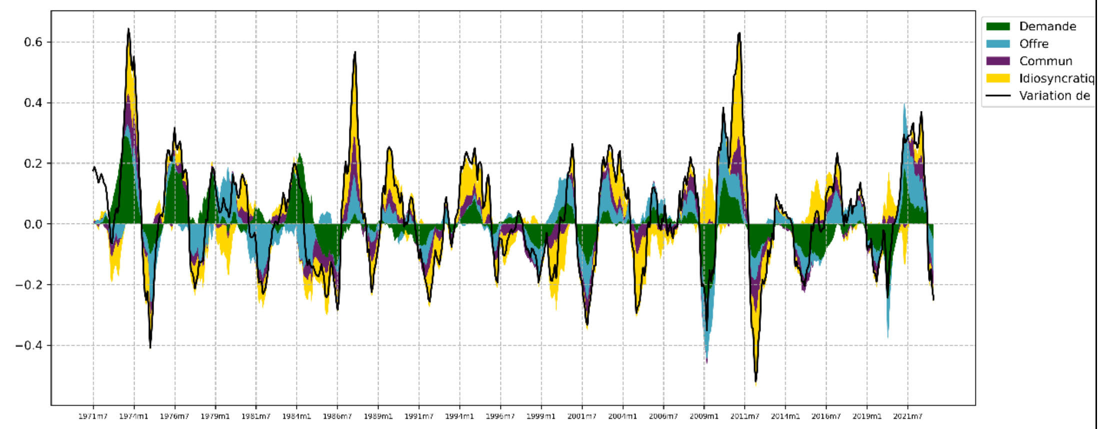
Crops considered by country

- Argentina: Maize, Soya
- Bangladesh: Rice
- Brazil: Cocoa, Coffee, Cane (sugar), Maize, Soya, Cotton, Bananas, Oranges
- Cameroon: Cocoa
- China: Cane (sugar), Wheat, Maize, Soya, Cotton, Bananas, Oranges, Apples, Tomatoes, Potatoes, Rice
- Colombia : Coffee
- Ivory Coast: Cocoa, Rubber
- France: Wheat
- Russian Federation: Wheat, Potatoes
- India: Cane (sugar), Rubber, Wheat, Soya, Cotton, Bananas, Oranges, Tomatoes, Potatoes, Rice
- Indonesia: Cocoa, Coffee, Rubber, Bananas, Rice
- Iran (Islamic Republic of): Apples
- Italy: Tomatoes
- Mexico: Oranges
- Nigeria: Cocoa, Bananas
- Pakistan: Cane (sugar), Cotton
- Peru: Coffee
- Thailand: Cane (sugar), Rubber
- Turkey : Apples, Tomatoes
- Ukraine : Maize, Potatoes
- Viet Nam : Coffee, Rubber, Rice
- United States of America : Wheat, Maize, Soya, Cotton, Oranges, Apples, Tomatoes, Potatoes

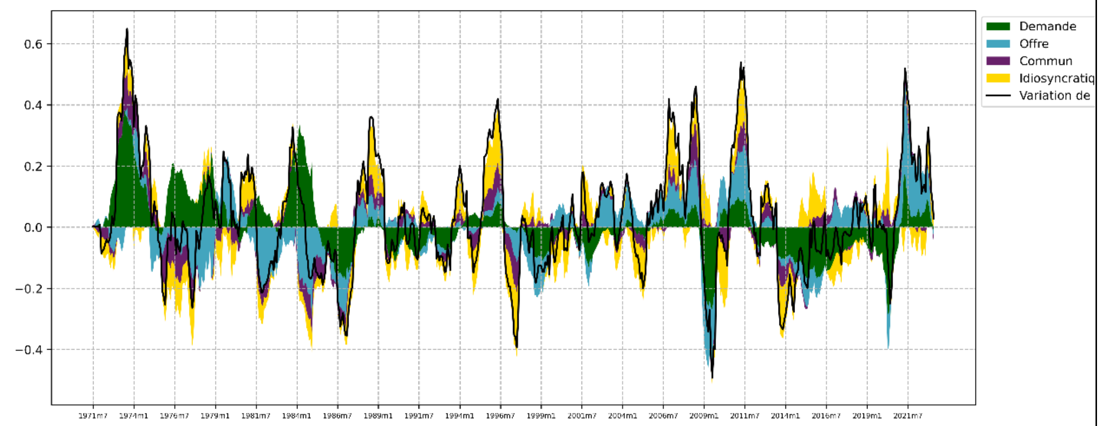
Appendix B - Historical decomposition based on the BVAR models

Figure A.1: Historical Decomposition of Prices for Annual Crops

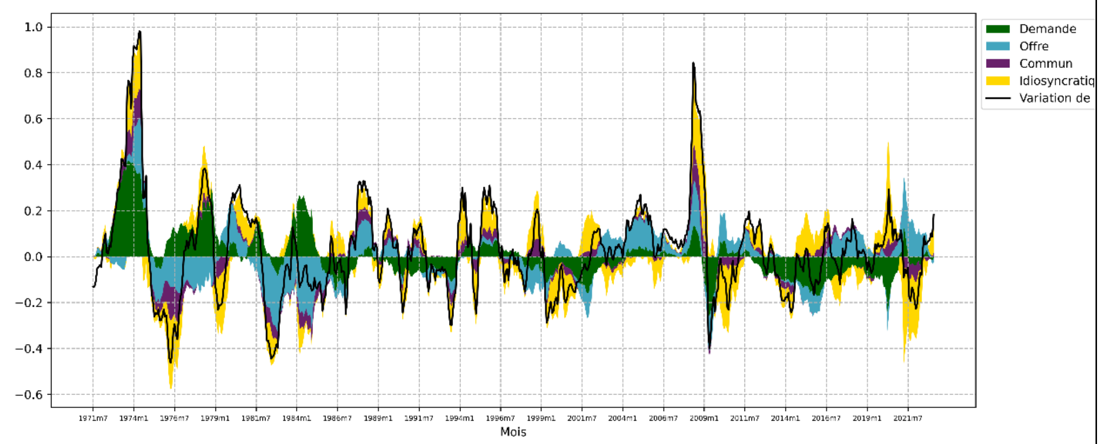
Cotton



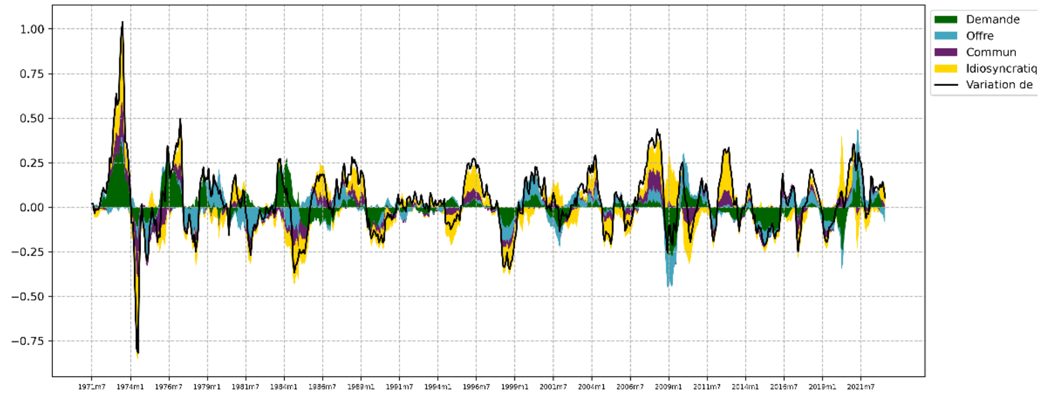
Maize



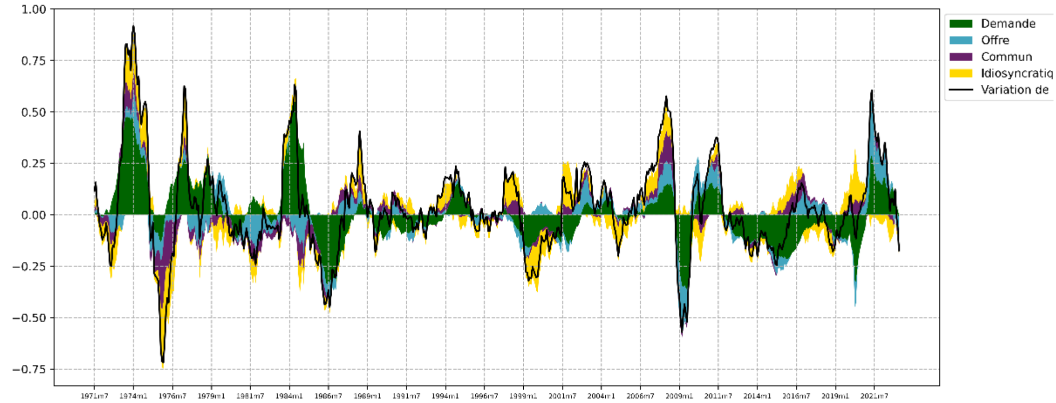
Rice



Soy (beans)



Soy (oil)



Wheat

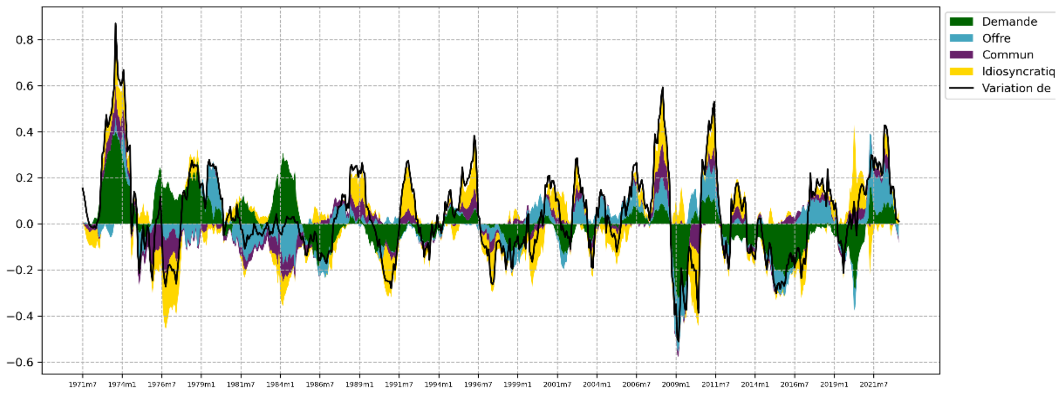
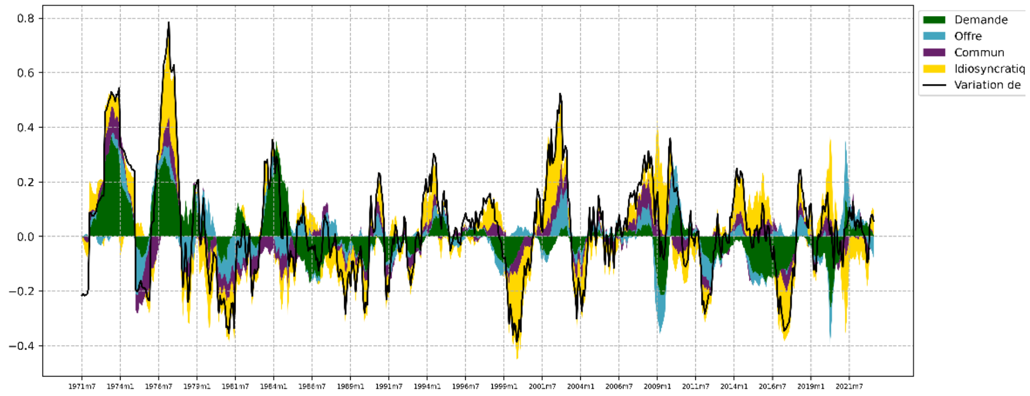
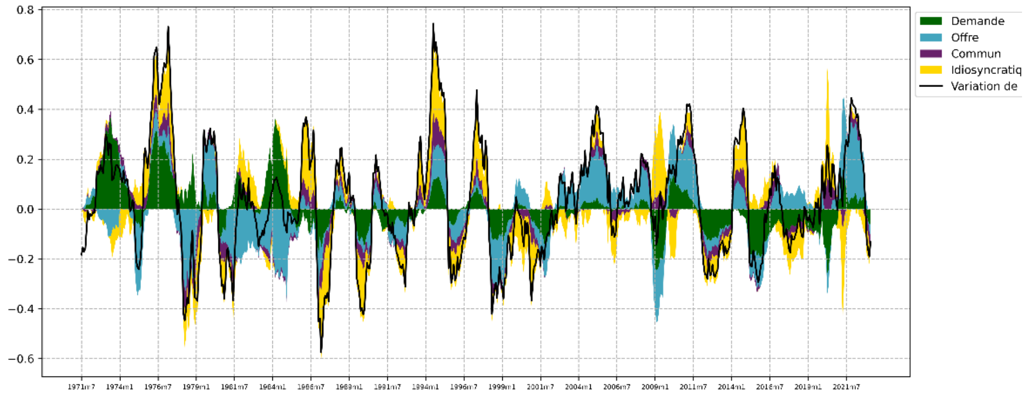


Figure A.2: Historical Decomposition of Prices for Perennial Crops

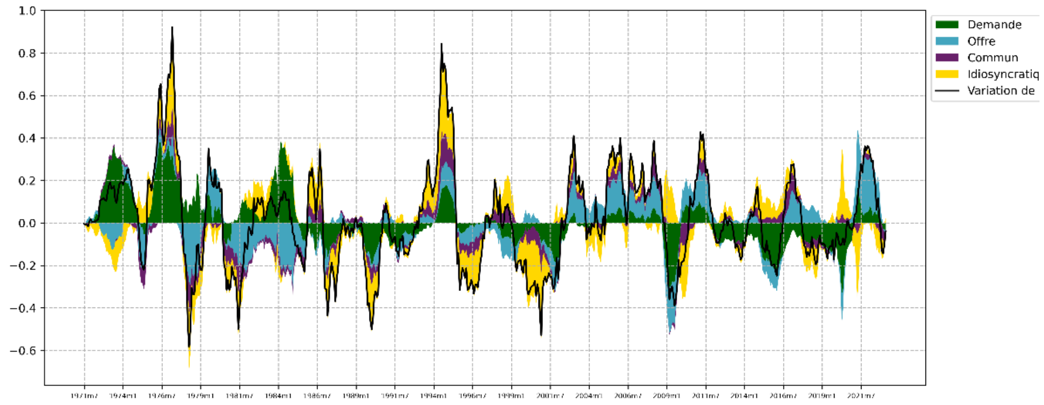
Cocoa



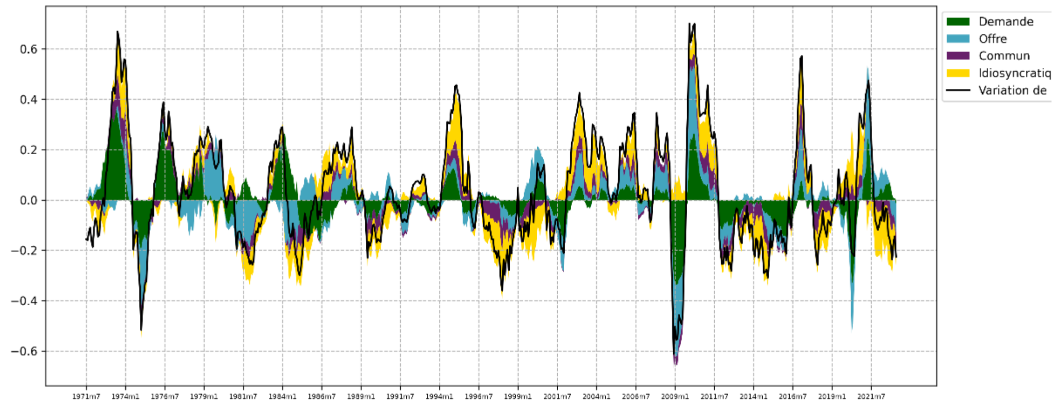
Arabica



Robusta



Rubber


Demande
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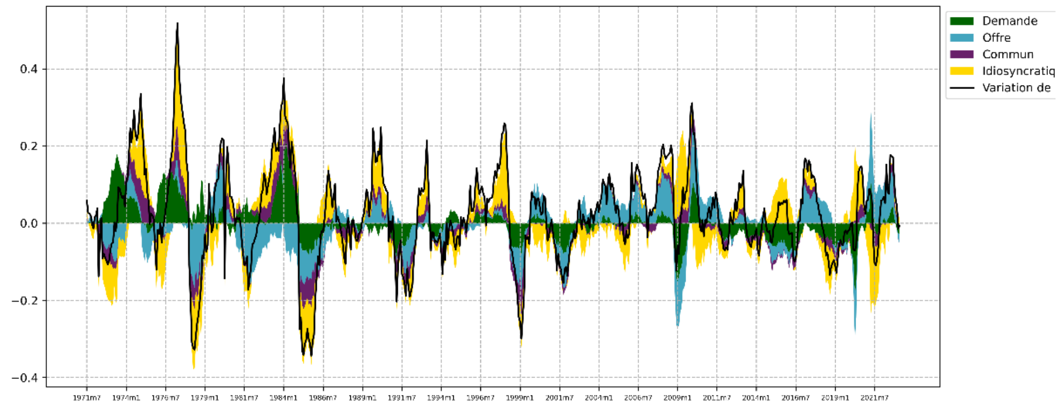
Variation de

Tea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Appendix C – Modelling HICP impacts

In our specification:

- bce_meat refers to meat futures prices (Eurosystem assumptions);
- bce_ttf refers to gas futures prices on the European TTF market (Eurosystem assumptions);
- bce_wheat refers to wheat futures prices (Eurosystem assumptions);
- dummy_covid is a dummy which is worth 1 from April 2020 to June 2021 and which controls for erratic movements in unprocessed food during confinement periods.

In the short-term specification (Table A.1), all variables are significant at the 10% level. The recall force (monthly) is very strong at -0.30 and the R^2 of the equation at 0.39, without being very large, is greater than that of the specification currently used in MAPI (0.20).

Tableau A.1 – Long-term equation

Dependent Variable: LOG(I_A_SA_FF11)
Method: Least Squares (Gauss-Newton / Marquardt steps)
Sample: 2014M01 2023M12
Included observations: 120
LOG(I_A_SA_FF11)=CCLT(1)+CCLT(2)*LOG(BCE_MEAT)+CCLT(3)*LOG(BCE_TTF)+CCLT(4)*LOG(BCE_WHEAT)+CCLT(5)*DUMMY_COVID+CCLT(6)*TREND

	Coefficient	Std. Error	t-Statistic	Prob.
CCLT(1)	3.413234	0.060196	56.70194	0.0000
CCLT(2)	0.100532	0.019551	5.141987	0.0000
CCLT(3)	0.027158	0.003073	8.838405	0.0000
CCLT(4)	0.011197	0.005973	1.874493	0.0634
CCLT(5)	0.028612	0.004447	6.434718	0.0000
CCLT(6)	0.002499	7.22E-05	34.59554	0.0000

R-squared	0.988236	Mean dependent var	4.724630
Adjusted R-squared	0.987720	S.D. dependent var	0.115879
S.E. of regression	0.012841	Akaike info criterion	-5.823653
Sum squared resid	0.018797	Schwarz criterion	-5.684279
Log likelihood	355.4192	Hannan-Quinn criter.	-5.767053
F-statistic	1915.375	Durbin-Watson stat	0.589808
Prob(F-statistic)	0.000000		

Table A.2 – Short term equation

Dependent Variable: D(LOG_I_A_SA)
Method: Least Squares (Gauss-Newton / Marquardt steps)
Sample: 2014M02 2023M12
Included observations: 119
D(LOG_I_A_SA)=CCCT(1)+CCCT(2)*(LOG_I_A_SA(-1)-3.41323402423986 -0.100531782033538*LOG_MEAT(-1)-0.0271575901573979 *LOG_TTF(-1)-0.0111969065331256*LOG_WHEAT(-1) -0.0286122515359153*DUMMY_COVID-0.00249940107802946 *TREND)+CCCT(3)*D(LOG_I_A_SA(-1))+CCCT(4)*D(LOG_I_A_SA(-2)) +CCCT(5)*D(LOG_TTF)

	Coefficient	Std. Error	t-Statistic	Prob.
CCCT(1)	0.001527	0.000779	1.959348	0.0525
CCCT(2)	-0.295906	0.059224	-4.996384	0.0000
CCCT(3)	0.464467	0.078408	5.923698	0.0000
CCCT(4)	-0.203265	0.084637	-2.401623	0.0179
CCCT(5)	0.010508	0.003772	2.786063	0.0063

R-squared	0.387351	Mean dependent var	0.003272
Adjusted R-squared	0.365854	S.D. dependent var	0.009137
S.E. of regression	0.007276	Akaike info criterion	-6.967446
Sum squared resid	0.006035	Schwarz criterion	-6.850676
Log likelihood	419.5630	Hannan-Quinn criter.	-6.920030
F-statistic	18.01927	Durbin-Watson stat	1.887180
Prob(F-statistic)	0.000000		

Tableau A.3 – Long-term equation

Dependent Variable: LOG(BCE_MEAT)
Method: Least Squares (Gauss-Newton / Marquardt steps)
Sample: 2014M01 2023M12
Included observations: 120
LOG(BCE_MEAT)=C(1)+C(2)*LOG(MAIS(-4))+C(3)*LOG(SOJA_FEVES)
+C(4)*LOG(BCE_TTF)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.364120	0.262821	5.190290	0.0000
C(2)	0.313739	0.059468	5.275753	0.0000
C(3)	0.162087	0.058134	2.788164	0.0062
C(4)	0.113705	0.013531	8.403430	0.0000

R-squared	0.783730	Mean dependent var	4.753250
Adjusted R-squared	0.778137	S.D. dependent var	0.188953
S.E. of regression	0.089001	Akaike info criterion	-1.967569
Sum squared resid	0.918861	Schwarz criterion	-1.874652
Log likelihood	122.0541	Hannan-Quinn criter.	-1.929835
F-statistic	140.1222	Durbin-Watson stat	0.174488
Prob(F-statistic)	0.000000		

Table A.4 – Short term equation

Dependent Variable: DLOG(BCE_MEAT)
Method: Least Squares (Gauss-Newton / Marquardt steps)
Sample: 2014M01 2023M12
Included observations: 120
DLOG(BCE_MEAT)=CCT(1)+CCT(2)*(LOG(BCE_MEAT(-1))
-1.3641197171342-0.31373923624827*LOG(MAIS(-5))
-0.162086876516253*LOG(SOJA_FEVES(-1))-0.113705321074542
*LOG(BCE_TTF(-1)))+CCT(3)*DLOG(BCE_MEAT(-1))+CCT(4)
*DLOG(MAIS(-1))+CCT(5)*DLOG(SOJA_FEVES)

	Coefficient	Std. Error	t-Statistic	Prob.
CCT(1)	0.001890	0.001929	0.979933	0.3292
CCT(2)	-0.054205	0.022256	-2.435524	0.0164
CCT(3)	0.490922	0.080123	6.127132	0.0000
CCT(4)	0.069155	0.036143	1.913397	0.0582
CCT(5)	0.077044	0.041779	1.844103	0.0677

R-squared	0.368649	Mean dependent var	0.004133
Adjusted R-squared	0.346689	S.D. dependent var	0.025719
S.E. of regression	0.020788	Akaike info criterion	-4.868111
Sum squared resid	0.049696	Schwarz criterion	-4.751965
Log likelihood	297.0867	Hannan-Quinn criter.	-4.820944
F-statistic	16.78728	Durbin-Watson stat	1.950882
Prob(F-statistic)	0.000000		

Appendix D - Transition risks: model calibration for Devulder & Lisack, 2020

Table A.5: elasticities of substitution

Labour, intermediate inputs and energy (θ)	0,5
Non-energy intermediate inputs (ϵ)	0,3
Imported vs domestic non-energy intermediate inputs (η_I)	1,5
Non-energy intermediate inputs imported from different countries (ξ_I)	2,5
Types of energy (σ)	1,2
Imported vs domestic energy (η_E)	2
Imported energy from different countries (ξ_E)	4
Final consumption (ρ)	0,8

References

Bauer, D. M., & Sue Wing, I. (2016). The macroeconomic cost of catastrophic pollinator declines. *Ecological Economics*, 126:1–13, .

Baumeister, C., & Hamilton, J. D. (2019). Structural Interpretation of Vector Autoregressions with Incomplete Identification: Revisiting the Role of Oil Supply and Demand Shocks. *American Economic Review,*, 109(5):1873–1910. .

Baumgärtner, S., Drupp, & Moritz A, Q. M. (2017). Subsistence, substitutability and sustainability in consumption. , . *Environmental and Resource Economics*, 67:47–66, .

Beckman, J., Ivanic, M., Jelliffe, J. L., Baquedano, F. G., & Scott, S. G. (2020). *Economic and Food Security Impacts of Agricultural Input Reduction Under the European Union Green Deal's Farm to Fork and Biodiversity Strategies.* U.S. Department of Agriculture, Economic Research Service.

Bellora, C., & Bourgeon, J.-M. (2019). Food Trade and Biodiversity Effects. *International Economic Review, 60(4),* , 1957–1999.

Bellora, C., & Bureau, J.-C. (2016). *How green is organic farming? Indirect effects of a greener European agriculture.* Presented at the 19th Annual Conference on Global Economic Analysis, Washington DC, USA.

Boldrini, S., Ceglar, A., & al., e. (2023). *Living in a world of disappearing nature: physical risk and the implications for financial stability. .* European Central Bank.

Bremmer, J., Gonzalez-Martinez, A., Jongeneel, R., Huiting, R., x Stokkers, R., & Ruijs, M. (2021). *Impact Assessment of EC 2030 Green Deal Targets for Sustainable Crop Production.* Wageningen: Wageningen Economic Research.

Bucheli, J., Visse-Mansiaux, M., Herrera, J., Levy Häner, L., Tack, J., & Finger, R. (2024). Precipitation causes quality losses of large economic relevance in wheat production. *Q Open*.

Calice, P., Diaz Kalan, F. A., Dunz, N. M., & Miguel Liriano, F. (2023). *Biodiversity and Finance : A Preliminary Assessment of Physical Risks for the BankingSector in Emerging Markets.* World Bank Policy Research Working Paper Series 1.

Calice, P., Diaz Kalan, F., & Miguel, F. (2021). *Nature-Related Financial Risks in Brazil. .* World Bank, Finance, Competitiveness and Innovation Global Practice.

Cerda, & al., e. (2017). Primary and Secondary Yield Losses Caused by Pests and Diseases: Assessment and Modeling in Coffee. *PLos One*, 12(1): e0169133. .

Dasgupta, P. (2021). *The economics of biodiversity: the Dasgupta review.* London:: HM Treasury.

de L'Estoile, E., & Salin, M. (2024). *Who Takes the Land? Quantifying the Use of Built-Up Land by French Economic Sectors to Assess Their Vulnerability to the 'No Net Land Take' Policy.* Banque de France Working Paper #941.

Dechezleprêtre, A., & Sato, M. (2017). The impacts of environmental regulations on competitiveness. *Review of Environmental Economics and Policy*, , 11(2), 183–206.

Devulder, A., & Lisack, N. (2020). *Carbon Tax in a Production Network: Propagation and Sectoral Incidence.* Banque de France Working Paper #670.

Díaz, S., Demissew, S., Carabias, J., Joly, C. A., & al., e. (2015). *The IPBES conceptual framework — Connecting nature and people. Current Opinion in Environmental Sustainability, .* IPBES.

Early, R., Gonzalez-Moreno, P., Murphy, S. T., & Day, R. (2018). Forecasting the global extent of invasion of the cereal pest spodoptera frugiperda, the fall armyworm. *BioRxiv*, 391847,.

FAO. (2015). *Status of the world's soil resources: main report.*

FAO. (2019). The State of the World's Biodiversity for Food and Agriculture.

FAO. (2021). *The impact of disasters and crises on agriculture and food security: 2021. .*

FAO. (2024). Cultures et produits animaux. Base de données en ligne . Retrieved Juin 2024

Gateau-Rey, & et al. (2018). Climate change could threaten cocoa production: Effects of 2015-16 El Nin˜o-related drought on cocoa agroforests in Bahia, Brazil. *PLoS ONE 13(7)*, e0200454.

Gouel, C., & Laborde, D. (2021). The crucial role of domestic and international market-mediated adaptation to climate change. *Journal of Environmental Economics and Management*.

Guest, & al., e. (2007). Black Pod: Diverse Pathogens with a Global Impact on Cocoa Yield. *Phytopathology*, 97:1650-1653.

Ha, J., Kose, M. A., & Ohnsorge, F. (2023). One-stop source: A global database of inflation. *Journal of International Money and Finance*, 137:102896.

IPBES . (2018a). *Regional assessment report on biodiversity and ecosystem services for Europe and Central Asia. .* Bonn, Germany.: Secretariat of the IPBES, .

IPBES. (2015). *The IPBES Conceptual Framework - connecting nature and people. Current Opinion in Environmental Sustainability, .* Díaz, S., Demissew, S., Carabias, J., Joly, C., Lonsdale, M., Ash, N., ... & Zlatanova, D.

IPBES. (2016). *The assessment report of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services on pollinators, pollination and food production. S.G. Potts, V. L. Imperatriz-Fonseca, and H. T. Ngo.* Bonn, Germany: Secretariat of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services,.

IPBES. (2019). *Summary for policymakers of the global assessment report on biodiversity and ecosystem services of the intergovernmental science-policy platform on biodiversity and ecosystem services.*

IPBES. (2019). *Summary for policymakers of the global assessment report on biodiversity and ecosystem services of the intergovernmental science-policy platform on biodiversity and ecosystem services.*

IPBES. (2023). *Summary for Policymakers of the Thematic Assessment Report on Invasive Alien Species and their Control of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. Roy, H. E., Pauchard, A., Stoett, P., Renard Truong, T., Bach.* Bonn, Germany: IPBES Secretariat.

Johnson, & al., e. (2010). Coffee Berry Borer (Hypothenemus hampei), a Global Pest of Coffee: Perspectives from Historical and Recent Invasions, and Future Priorities. *Insects*, 11, 882;.

Johnson, J. A., Ruta, G., Baldos, U., & al., e. (2021). *The Economic Case for Nature: A Global Earth-Economy Model to Assess Development Policy Pathways.* The World Bank.

Klein, A., Vaissière, B., Cane, J., Steffan-Dewenter, I., Cunningham, S., & Kremen, C. :. (2006). Importance of pollinators in changing landscapes for world crops. *Proceedings. Biological sciences / The Royal Society*, 274:303–13.

Li, W., Zhang, R., Huang, Y., Pu, C., Yin, J., XY, C., . . . ZM, L. (2017). Loss of cane and sugar yield resulting from Ceratovacuna lanigera Zehntner damage in cane-growing regions in China. *Bulletin of Entomological Research*, 108(1):125-129.

Losey, J. E., & Vaughan, M. (2006). The economic value of ecological services provided by insects. *Bioscience,*, 56(4):311–323.

Najeeb, & al., e. (2015). AoB PLANTS. *Consequences of waterlogging in cotton and opportunities for mitigation of yield losses* .

NGFS & INSPIRE. (2022). *Central banking and supervision in the biosphere: An agenda for action on biodiversity loss, financial risk and system stability.*

NGFS. (2023). *NGFS recommendations toward the development of scenarios for assessing nature-related economic and financial risks.*

NGFS. (2023a). *Conceptual Framework for nature-related financial risks.*

NGFS. (2023b). *Recommendations toward the development of scenarios for assessing nature-related economic and financial risks.*

OECD. (2021). *Assessing the Economic Impacts of Environmental Policies: Evidence from a Decade of OECD Research. .* OECD Publishing.

Oerke, E.-C. (2006). Crop losses to pests. *The Journal of agricultural science*, , 144(1):31–43, .

Paini, D. R., Sheppard, A. W., Cook, D. C., De Barro, P. J., Worner, S. P., & Thomas, M. B. (2016). Global threat to agriculture from invasive species. *Proceedings of the National Academy of Sciences*, 113(27):7575–7579.

Panigrahi, & al., e. (2020). Identifying opportunities to improve management of water stress in banana production . *Scientia Horticulturae,*.

Potts, S., Imperatriz-Fonseca, V., Ngo, H. T., Aizen, M., Biesmeijer, J., Breeze, T., . . . Salles, J.-M. (2016). Safeguarding pollinators and their values to human well-being. *Nature*, 540, 11.

Pozebon, & al., e. (2020). Arthropod invasions versus soybean production in brazil: a review. . *Journal of economic entomology* , 1591–1608 .

Ranger, N., Alvarez, J., Freeman, A., Harwood, T., Obersteiner, M., Paulus, E., & Sabuco., J. (2023). *The green scorpion: The macro-criticality of nature for finance: Foundations for scenario-based analysis of complex and cascading physical nature-related financial risks.*

Ranger, N., Oliver, T., & al., e. (2024). *Assessing the Materiality of Nature-Related Financial Risks for the UK,.* he Green Finance Institute.

Rezaei, E. E., Webber, H., Asseng, S., Boote, K., Durand, J. L., Ewert, F., . . . MacCarthy, D. S. (2023). Climate change impacts on crop yields. *Nature Reviews Earth & Environment*, 4(12):831–846, .

Roy, H. E., Pauchard, A., Stoett, P., & Renard Truong, T. (2024). *IPBES Invasive Alien Species Assessment: Full Report.*

Savary, S., Willocquet, L., Pethybridge, S. J., Esker, P., McRoberts, N., & NElson, A. (2019). The global burden of pathogens and pests on major food crops. *Nature ecology & Evolution*, 3(3):430–439.

Seebens, H., Bacher, S., Blackburn, T. M., Capinha, C., Dawson, Wayne, D. S., . . . al., e. (2021). Projecting the continental accumulation of alien species through to 2050. *Global Change Biology*, 27(5):970–982.

Steduto, P., Hsiao, T. C., Fereres, E., & Raes, D. (2012). Crop yield response to water. *FAO Irrigation and drainage*.

Svartzman, R., & et al. (2021). *A "Silent Spring" for the Financial System? Exploring Biodiversity-Related Financial Risks in France.* Banque de France Working Paper #826.

Ulgazi, Y., & Vertier, P. (2022). *Forecasting Inflation in France: an Update of MAPI.* Working Paper Banque de France.

Van Toor, J., Piljic, D., Schellekens, G., van Oorschot, M., & Kok, M. (2020). *Indebted to Nature: Exploring Biodiversity Risks for the Dutch Financial Sector.* De Nederlandsche Bank and PBL Netherlands Environmental Assessment Agency.

World Economic Forum. (2020). *Nature Risk Rising: Why the Crisis Engulfing Nature Matters for Business and the Economy (New Nature Economy Report I). .* In collaboration with PwC.