

An analysis of biodiversity and the macroeconomy of China

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Abstract

As one of the most biodiverse nations globally, China is also among the countries most severely threatened by biodiversity loss. As a core component of ecosystems, biodiversity provides irreplaceable ecological, economic, and social value to human society. However, the rate of species extinction driven by socio-economic activities has far exceeded natural background levels. In recent years, growing attention has been paid to the biodiversity footprints of socio-economic activities. Nevertheless, most of the existing studies remain confined to static analyses based on extended input-output frameworks, neglecting the endogenous dynamics of the macroeconomy and lacking systematic policy evaluation. To address these limitations, this paper develops a multi-regional input-output stock-flow model, termed “CHIMERA” (CHIna Macro-(IO-SFC)-Ecological Resource Accounting), which provides a dynamic framework to study the linkage between biodiversity and the macroeconomy in China, as well as for evaluating the effectiveness of policy toolkits through scenario simulations. The model incorporates 31 provinces, 7 industrial sectors and 5 institutional sectors, namely, non-financial corporations, banks, governments, households and the rest of the world. Institutional behaviours are empirically estimated based on the national balance sheet and transaction flow matrix data from 1992 to 2023, enabling a comprehensive representation of China’s macroeconomic and industrial structure. Building upon the existing literature, we construct the species threat coefficient to quantify bird species footprints across regions and sectors, covering 129 threatened bird species. Given the lack of a unified metric for the severity of different threat drivers, the analysis is restricted to threatened bird species to mitigate the bias arising from the assumption of homogeneous threat severity across species. The model further enables a systematic attribution of ecological responsibility for biodiversity loss, revealing the heterogeneous distribution of responsibility across regions and sectors within the Chinese economy. Then, we run a regulation scenario implemented from 2026, referring to the Ecological and Environmental Code of the People’s Republic of China. Comparative results indicate that regulatory policies can effectively protect the bird species, but at the cost of constraining high-impact industries, thereby generating supply-side contraction effects and leading to a decline in gross domestic product (GDP). Lastly, we run a structural change scenario with fiscal policies targeting less bird-threatening industries and regions and show that industrial and regional policies can moderate the economic cost of the regulation and generate a smoother structural transition to protect bird species.

Keywords: stock-flow consistent model, biodiversity conservation, regulation, multi-regional input-output

JEL codes: E17, Q57, Q58, R15

1 Introduction

Roughly a quarter of the world’s species currently face extinction risk, and the pace of loss has accelerated over the past five decades despite a proliferation of international agreements and national conservation commitments (Kass, 2020). The proximate causes are well documented: habitat destruction from agricultural expansion, pollution, invasive species, and climate change. Less well understood is the relationship between these pressures and the economic structures that generate them, and less well understood still is what happens to those economic structures when you try to reduce the pressures.

The input-output literature has made genuine progress on the first of these questions. By appending environmental satellite accounts to standard Leontief frameworks, it is now possible to trace how a unit of

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final demand in one sector or region propagates through supply chains and ultimately generates pressure on ecosystems. Applied to biodiversity, this approach has identified agriculture, food processing, and extractive industries as the dominant contributors across a range of national and global assessments (Lenzen et al., 2012; Wilting et al., 2017). For China specifically, Zhang et al. (2024) map the inter-provincial network of biodiversity loss and show that Yunnan, Tibet, Guangdong, and Sichuan collectively account for more than 40 percent of the national footprint, a concentration that reflects both ecological endowment and the structure of domestic trade. H. Wang et al. (2025) extend this to a full provincial-sector dataset covering nearly 450 threatened and near-threatened species, confirming the primacy of agriculture while revealing substantial variation across regions that aggregate national estimates tend to obscure.

What this literature cannot do is simulate a policy. The Leontief model takes final demand as given and solves mechanically for gross output. There is no investment function, no household budget constraint that responds to changes in income or interest rates, no government that must finance its expenditures, no bank that extends or withdraws credit. This is not a criticism of work that was never designed to address these questions. But it does mean that when a government introduces regulation that constrains a set of industries, input-output analysis can tell you how much output those industries currently produce and how much biodiversity loss is attributed to them. It cannot tell you what the economy looks like five or ten years later, once firms have adjusted their capital stocks, households have revised their consumption plans, and the financial system has absorbed the shock.

This matters particularly for China. The country has adopted an ambitious regulatory agenda through its Ecological and Environmental Code, which imposes binding constraints on industrial activities judged harmful to natural systems. This agenda sits squarely within the broader priorities of the 15th Five Year Plan (2026-2030), which places clean energy transition and environmental protection at the centre of China’s development strategy. The regulation scenario we simulate is therefore not a thought experiment but a direct engagement with policy that is already being designed and will be implemented within our projection horizon (Congress, 2026; Council, 2026). China is also a particularly important case for biodiversity economics. It is one of the most biodiverse nations on earth — Yunnan alone harbours more than half the country’s animal and plant species on roughly four percent of its land (Zhang et al., 2024) — and one of the most economically dynamic, with a production structure that has shifted rapidly across regions and sectors over the past three decades. How ecological pressure and structural economic change interact over time, and what policy can do about it, cannot be addressed with a framework that holds output fixed.

Stock-flow consistent (SFC) models, developed within the post-Keynesian tradition by Godley and Lavoie (2006) among others, provide the accounting architecture to do this. They track financial stocks and flows across institutional sectors through balance sheets and transaction matrices, ensuring that every asset corresponds to a liability and every income has both a source and a destination. Coupled with behavioural equations for households, firms, banks, governments, and the rest of the world, they produce dynamic models capable of tracing how an economy adjusts over time in response to shocks or policy changes. Their limitation, for present purposes, is that they operate at a high level of aggregation and carry no spatial or sectoral detail on environmental pressures.

We therefore combine the two frameworks. The model we develop — CHIMERA — embeds a multi-regional input-output structure covering 31 Chinese provinces and seven industrial sectors, comprising five final demand-oriented sectors, a manufacturing sector as the sole downstream industry, and a residual others sector, within a national SFC model comprising five institutional sectors: non-financial corporations, banks, governments, households, and the rest of the world. Behavioural parameters are estimated empirically using balance sheet and transaction flow data from 1992 to 2022. Biodiversity footprints are constructed by region and sector for 129 threatened and near threatened bird species, using threat coefficients following H. Wang et al. (2025) and Zhang et al. (2024). The focus on birds reflects data quality rather than ecological priority: the International Union for Conservation of Nature (List et al., 2004) coverage for this taxonomic group is sufficiently detailed to support credible threat attribution at the sector level, whereas extending the analysis to taxa with sparser records would require assumptions that would swamp the model’s precision.

Three scenarios are run against a business-as-usual baseline projected from 2017 to 2031. A sensitivity scenario to test the sensitivity of bird footprint to aggregate demand components. A regulation scenario introduces the constraints of China’s Ecological and Environmental Code from 2026 and traces the resulting ecological and macroeconomic trajectories. A structural change scenario adds targeted fiscal policies designed to redirect activity toward less ecologically damaging industries and regions, testing whether the economic cost of regulation can be moderated without compromising its conservation

objectives. The comparison across these scenarios is the central empirical contribution of the paper.

The rest of the paper proceeds as follows. Section 2 reviews the relevant literature on biodiversity footprints and MRIO modelling for China. Section 3 presents stylised facts from the Chinese input-output tables that inform the calibration. Section 4 describes the model. Section 5 details data sources and calibration choices. Section 6 reports simulation results. Section 7 concludes.

2 Literature review

Biodiversity loss has become one of the major global environmental crises, driven largely by land-use change, agricultural expansion, and increasing consumption. Economic globalisation has intensified the indirect linkages between consumption in one region and environmental impacts in another, captured by the so-called Environmentally Extended Input-Output (EEIO) approach. In what follows, we will focus on biodiversity loss to narrow the analysis closer to the aim of the present study. The EEIO approach has identified agriculture, food processing, and extractive industries as the dominant contributors across a range of national and global assessments (Lenzen et al., 2012; Wilting et al., 2017). For China specifically, Zhang et al. (2024) map the inter-provincial network of biodiversity loss and show that Yunnan, Tibet, Guangdong, and Sichuan collectively account for more than 40% of the national footprint, a concentration that reflects both ecological endowment and the structure of domestic trade. H. Wang et al. (2025) extend this to a full provincial-sector dataset covering nearly 450 threatened and near-threatened species, confirming the primacy of agriculture while revealing substantial variation across regions that aggregate national estimates tend to obscure. Kulionis et al. (2024) combined EE-MRIO life cycle assessment (LCA) techniques to show that the most responsible area for biodiversity loss are America and Asia; while the main drivers were land use, followed by water stress and climate change. Sun et al. (2026), using the Food and Agriculture Biomass Input-Output database for China (FABIO-CHN), database found that consumption in China’s economically advanced eastern provinces drives significant biodiversity impacts in less-developed but species-rich southwestern regions like Yunnan and Sichuan. Animal product consumption, especially beef and mutton, contributes disproportionately to biodiversity loss, underlining the importance of dietary and consumption-side policy interventions.

Beyond this, the recognition of the heterogeneous spatial distribution of socio-ecological variables pushed researchers to build new multi-regional input-output (MRIO) data, including provincial extensions. In China, efforts in this direction were remarkable (Zheng et al., 2021; Hou et al., 2025; J. Li et al., 2026). The MRIO framework, rooted in Leontief’s input-output theory, quantifies how economic activities in one region depend on and affect production in others, making it particularly suitable for assessing embodied environmental impacts (energy and material use, pollution, etc.) in traded goods. The development of provincial MRIO tables in China has advanced significantly, enabling detailed sub-national analyses. Databases such as those compiled by Mi et al. (2018), Zheng et al. (2021), and J. Li et al. (2026) use gravity and cross-entropy methods to estimate interprovincial trade flows. Yue et al. (2023) applied EE-MRIO at the global scale, together with structural path analysis and social network analysis, showing that agriculture is the most relevant sector responsible for biodiversity loss and that while most of the footprint of biodiversity loss occurs within the region, a significant impact is due to global production chains outside the region. L. Wang et al. (2025) developed a species threat satellite account coupled with a MRIO model to assess biodiversity footprints in China, finding that regions with high biodiversity footprints were concentrated in ecologically vulnerable southwestern areas. Zhang et al. (2024) confirmed that eastern and coastal areas are the final drivers of biodiversity loss in China, driven by increasingly complex trade links. Xu et al. (2025) combined MRIO with LCA to quantify China’s biodiversity losses driven by global consumption, and highlighted the disproportionate environmental burdens borne by different provinces.

More recently, subnational-international coupling (SIC) MRIO models have emerged, linking provincial Chinese data to global trade networks. This integration captures the dual domestic-international nature of China’s economy, revealing how both internal demand and exports influence biodiversity hotspots. Recent studies have focused on integrating biodiversity indicators into MRIO analysis to capture the ecological consequences of consumption.

Overall, the literature converges on several key insights: biodiversity loss is deeply embedded in production-consumption systems; spatially explicit MRIO models are essential for attributing responsibility across regions; and China’s case demonstrates the tension between rapid economic growth and ecological conservation.

3 Stylised facts

Figure 1 shows the provincial distribution of bird footprint. We can observe that the provinces in the South West, Yunnan and Sichuan, and Xinjiang in the North West contribute the majority of bird footprint. However, it should be noted that these provinces are also the main habitat of threatened and near-threatened bird species (H. Wang et al., 2025). Consequently, we cannot simply claim they hold the main responsibility in threatening bird species based on the bird footprint.

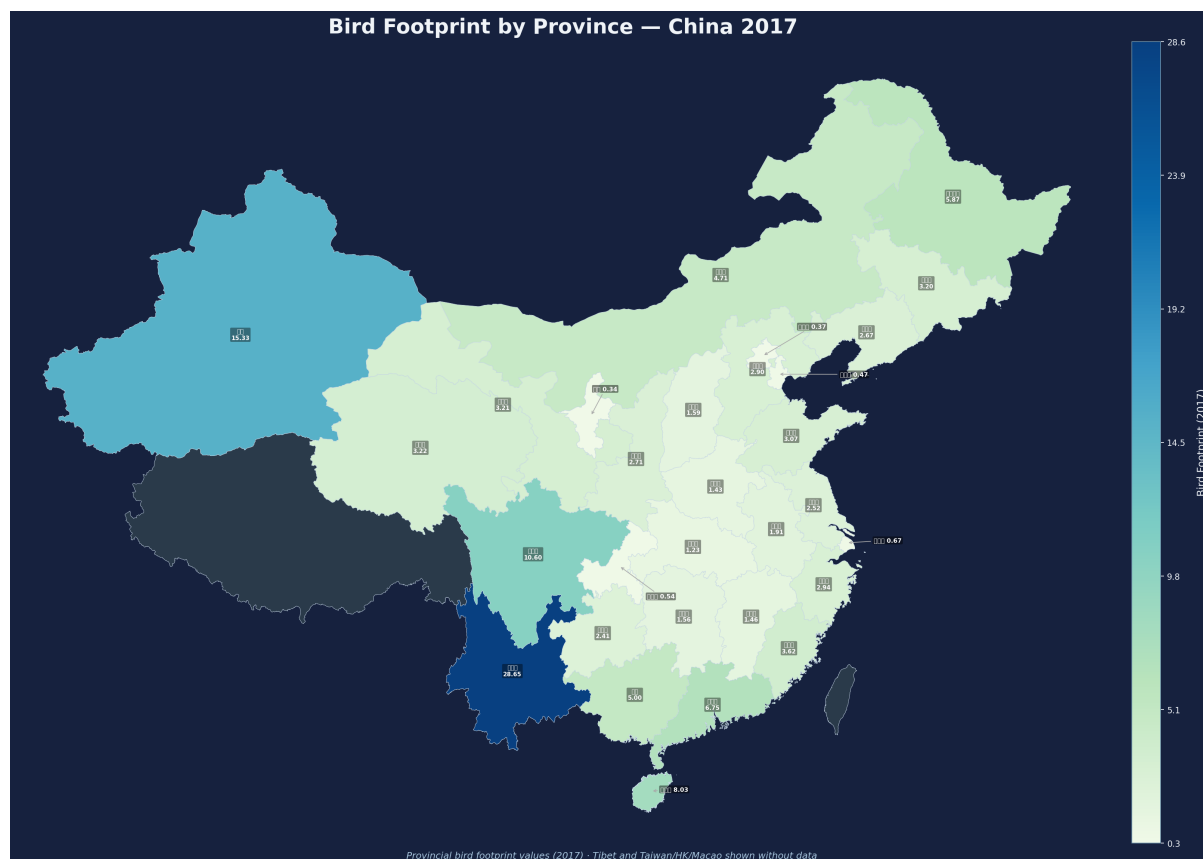


Figure 1: Bird province by province in 2017

Source: calculated based on H. Wang et al. (2025).

Regarding the industrial bird footprint, the top 5 industries are, 1) Agriculture, hunting, forestry, logging and related services, 2) Construction, 3) Transport, storage, and postal services, 4) Scientific research and polytechnic services, 5) Administration of water, environment, and public facilities, which contribute around 75% of total bird footprint (Table 1).

Table 1: Bird footprint by industry in 2017

Industries	Bird footprint (Total = 129)	Share
Agriculture, Forestry, Animal Husbandry and Fishery	59.81	0.4636
Transport, storage, and postal services	16.39	0.127
Construction	9.44	0.0732
Scientific research and polytechnic services	5.92	0.0459
Administration of water, environment, and public facilities	5.13	0.0397
Others	32.32	0.2505

Source: calculated based on H. Wang et al. (2025).

Based on the MRIO table, we rank the bird threaten upstream industries by the demand on total intermediate goods of the bird threaten industries, i.e. the top 5 industries shown in Table 1, in order to have a view on the indirect effect of industries to bird footprint (Table 2). Excluding the bird threaten

industries themselves, manufacturing is the only industry stands out, accounting 42% of the total demand on the bird threaten industry intermediate goods.

Table 2: Bird threaten downstream industries in 2017

Industries	Bird threaten industry intermediate goods (100 million rmb)	Share
Manufacturing	82672.47	0.4197
Construction	32975.61	0.1674
Transport, storage, and postal services	21192.94	0.1076
Agriculture, Forestry, Animal Husbandry and Fishery	17663.8	0.0897
Scientific research and polytechnic services	9276.64	0.0471
Others	33192.49	0.1685

Source: calculated based on CEADs (Zheng et al., 2021).

4 The model

We include 31 Chinese direct-administered municipalities and provinces, namely, Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang,¹ indexed in r . And we include 7 industrial sectors in our model based on their importance on bird species footprint, namely, 1) Agriculture, hunting, forestry, logging and related services, 2) Manufacturing, 3) Construction, 4) Transport, storage, and postal services, 5) Scientific research and polytechnic services, 6) Administration of water, environment, and public facilities, and 7) Other, indexed in $i = agri, manu, con, tran, scien, admin, oth$.

The main mechanism of the model is as follows, the macroeconomic model, i.e. stock-flow consistent model, determined the aggregate final demand; the final demand is then distributed by industry and region, and derive the domestic output by industry and region through the MRIO model; and, finally, we derive the bird specie footprints of each industry and region through the threat coefficient matrix.

4.1 Bird specie footprints

We employed the biodiversity dataset from H. Wang et al. (2025) and focus on the bird species only, 88 threatened and 41 near threatened.

Bird specie footprint, $Q_{i,r,s,t}$, by industry and region depends on the bird specie threat coefficients by industry and region, $q_{i,r,s}$, and domestic output in volume by industry and region, $dop_{i,r,t}$, (Zhang et al., 2024; H. Wang et al., 2025),

$$Q_{i,r,s,t} = q_{i,r,s} dop_{i,r,t}. \quad (1)$$

4.2 The multi regional input-output (MRIO) model

We employed the MRIO dataset from CEADs (Zheng et al., 2021) for year 2017 and aggregate the industrial sectors and regions (see Table 3).

Table 3: MRIO table

	Industries×Regions	Final demand	Total output
Industries×Regions	$z_{i,r,i',r'}$	$fd_{i,r}$	$top_{i,r}$
Intermediate imports	$zr_{i,r}$		
Final imports	$m_{i,r}$		
Gross value added	$va_{i,r}$		
Total input	$tip_{i,r}$		

¹Hongkong, Macau and Taiwan are not included due to lack of data.

By definition, we derive the domestic output in volume by industry and region by subtracting the final and intermediate imports in volume by industry and region, $m_{i,r,t}$ and $zr_{i,r,t}$, respectively, from total output in volume by industry and region, $top_{i,r,t}$,

$$dop_{i,r,t} = top_{i,r,t} - m_{i,r,t} - zr_{i,r,t}. \quad (2)$$

Assuming a Leontief production function of the intermediate goods, total output in volume by industry and region follows,

$$top_{i,r,t} = (I - A_{i,r,i',r'})^{-1} fd_{i,r,t}, \quad (3)$$

where $A_{i,r,i',r'}$ denotes a 49×49 matrix of the domestic intermediate good productivity coefficients by industry and region to industry and region, and $fd_{i,r,t}$ denotes the final demand in volume by industry and region, which is the sum of household consumption, government consumption, non-financial asset formations and exports in volume by industry and region, $c_{h,i,r,t}$, $c_{g,i,r,t}$, $i_{i,r,t}$ and $x_{i,r,t}$, respectively,

$$fd_{i,r,t} = c_{h,i,r,t} + c_{g,i,r,t} + i_{i,r,t} + x_{i,r,t}. \quad (4)$$

Following the same assumption, intermediate imports in volume by industry and region are demanded by their productivity coefficients, $ar_{i,r}$,

$$zr_{i,r,t} = ar_{i,r} top_{i,r,t}. \quad (5)$$

Household consumption, government consumption, non-financial asset formations, exports, and final imports in volume by industry and region are distributed from aggregate household consumption, government consumption, non-financial asset formations, exports by industry and final imports in volume by their industrial and regional shares (see Appendix).

4.3 The stock-flow consistent model

The national economy comprises 5 institutional sectors, non-financial corporations, banks, governments, households and the rest of the world (RoW) (Table 5 and 6). Since we do focus not on the financial market, we keep the financial account minimal as possible but keeping the essential instruments of each sectors to close their financial constraints.

Table 5: The national balance sheet

	Firms	Banks	Governments	Households	RoW	Total
Non-financial assets	$+K_f$	$+K_b$	$+K_g$	$+K_h$		$+K$
International reserves		$+G$			$-G$	0
Deposits		$-D$		$+D$		0
Bonds		$+B$	$-B$			0
Loans	$-L_f$	$+L$		$-L_h$		0
Unlisted shares		$-E_b$	$+E_b$			0
Other accounts payable/receivable	$+Z_f$	$+Z_b$	$+Z_g$	$+Z_h$	$+Z_r$	0
Net worth	$-V_f$	0	$-V_g$	$-V_h$	$-V_r$	$-K$
Total	0	0	0	0	0	0

Note: + denotes assets, - denotes liabilities and equities.

The following subsections present the main equations of the institutional sectors. Behaviour equations follow the Post-Keynesian macroeconomic theory (e.g. Godley and Lavoie, 2006) and are pragmatically verified by econometrics employing historical annual data from 1992 to 2002 (National Bureau of Statistics, China's National Balance Sheet and World Bank).²

4.3.1 Final good market

Final good production, Y_t , fulfills the aggregate demand, which consists of households consumption, $C_{h,t}$, government consumption, $C_{g,t}$, gross non-financial asset formations by sectors, $I_{s,t}$, with $s =$

²Our method is pragmatic in the sense that we try to follow economic theories as closely as possible but drop the determinants in the behaviour equations that are not statistically significant.

Table 6: Transaction flow matrix

	Final goods	Firms	Banks	Governments	Households	RoW	Total
GDP	$-Y$	$+Y_f$	$+Y_b$	$+Y_g$	$+Y_h$		0
Consumption	$+C$			$-C_g$	$-C_h$		0
Investments	$+I$	$-I_f$	$-I_b$	$-I_g$	$-I_h$		0
Export	$+X$					$-X$	0
Import	$-M$					$+M$	0
Wages		$-W_f$		$-W_g$	$+W - W_h$		0
Net taxes on production		$-VAT$		$+VAT$			0
Interest on deposits			$-r_d D_{-1}$		$+r_d D_{-1}$		0
Interest on bonds			$+r_b B_{-1}$	$-r_b B_{-1}$			0
Interest on firm loans		$-r_{lf} L_{f,-1}$	$+r_{lf} L_{f,-1}$		$-r_{lh} L_{h,-1}$		0
Interest on household loans			$+r_{lh} L_{h,-1}$		$-r_{lh} L_{h,-1}$		0
Bank profits			$-BP$	$+BP$			0
Social contributions				$+SC$	$-SC$		0
Social benefits				$-SB$	$+SB$		0
Other current transfers		$-O_f$		$-O$	$+O_h$		0
Errors and omissions	$+EO$	$-EO_f$	$-EO_b$	$-EO_g$	$-EO_h$	$-EO_r$	0
Changes in reserves			$-\Delta G$			$+\Delta G$	0
Changes in deposits			$+\Delta D$		$-\Delta D$		0
Changes in bonds			$-\Delta B$	$+\Delta B$			0
Changes in loans		$+\Delta L_f$	$-\Delta L$		$+\Delta L_h$		0
Changes in unlisted shares			$+\Delta E_b$	$-\Delta E_b$			0
Changes in other accounts payable/receivable		$-\Delta Z_f$	$-\Delta Z_b$	$-\Delta Z_g$	$-\Delta Z_h$	$-\Delta Z_r$	0
Total	0	0	0	0	0	0	0

Note: + denotes transactions received, - denotes transactions paid.

f, b, g, h denotes the indices of firms (non-financial corporations), banks, governments and households, respectively, net exports, $X_t - M_t$, and errors and omissions, EO_t ,

$$Y_t = C_{h,t} + C_{g,t} + I_{f,t} + I_{b,t} + I_{g,t} + I_{h,t} + X_t - M_t + EO_t. \quad (6)$$

Aggregate demand in real term (in volume),

$$y_t = c_{h,t} + c_{g,t} + i_{f,t} + i_{b,t} + i_{g,t} + i_{h,t} + x_t - m_t + eo_t, \quad (7)$$

where $c_{h,t} = \frac{C_{h,t}}{P_{c,t}}$ and $c_{g,t} = \frac{C_{g,t}}{P_{c,t}}$ denotes household and government consumption in volume, respectively, $P_{c,t}$ denotes the consumer price index, $i_{s,t} = \frac{I_{s,t}}{P_{k,t}}$, for $s \neq h$, denotes firm, bank and government gross non-financial asset formations in volume, $P_{k,t}$ denotes the price of non-financial assets, $i_{h,t} = \frac{I_{h,t}}{P_{kh,t}}$ denotes household gross non-financial asset formations (mainly dwelling acquisitions), $P_{kh,t}$ denotes the nominal housing price index, $x_t = \frac{X_t}{P_{x,t}}$ denotes exports in volume, $P_{x,t}$ denotes the export price index, $m_t = \frac{M_t}{P_{m,t}}$ denotes imports in volume, $P_{m,t}$ denotes the import price index. By definition, GDP deflator, $P_{y,t} = \frac{Y_t}{y_t}$, with $eo_t = \frac{EO_t}{P_{y,t}}$.

Producers fulfill the aggregate demand but set their prices according to the cost of production, i.e. unit cost of production. The consumer price index,

$$\Delta \ln P_{c,t} = p_{c1} \Delta \ln \frac{W_{t-1} + VAT_{t-1} + M_{t-1}}{y_t}, \quad (8)$$

where W_t denotes the total wage bill, VAT_t denotes net production taxes, $0 < p_{c1} < 1$ is the elasticity of CPI to unit production cost.

The price of non-financial assets,

$$\ln P_{k1,t} = p_{k1} \Delta \ln \frac{W_{t-1} + VAT_{t-1} + M_{t-1}}{y_t}, \quad (9)$$

where $0 < p_{k1} < 1$ is the sensitivity of non-financial asset price to unit production cost growth.

Real housing price, as an exception, is mainly driven by housing demand,

$$\Delta \ln \frac{P_{kh,t}}{P_{y,t}} = p_{kh0} + p_{kh1} \Delta \ln i_{h,t}. \quad (10)$$

where p_{kh0} is the autonomous real housing price growth and $p_{kh1} > 0$ is sensitivity of real housing price growth to housing acquisition in volume growth.

Export price is also affected by the nominal exchange rate, xr_t (rise = appreciation, Goldberg and Knetter, 1996),

$$\Delta \ln P_{x,t} = p_{x1} \Delta \ln \frac{W_{t-1} + VAT_{t-1} + M_{t-1}}{y_t} + p_{x2} \Delta \ln xr_t, \quad (11)$$

where $0 < p_{x1} < 1$ denotes the elasticity of export price to unit production cost and $p_{x2} < 0$ denotes the elasticity of export price to the exchange rate.

Import price is determined by foreign price, $P_{r,t}$, assumed exogenous, and the nominal exchange rate (Goldberg & Knetter, 1996),

$$\Delta \ln P_{m,t} = p_{m1} \Delta \ln P_{r,t} + p_{m2} \Delta \ln xr_t, \quad (12)$$

where $p_{m1} > 0$ denotes the elasticity of import price to foreign price and $p_{m2} < 0$ denotes the elasticity of import price to the exchange rate.

4.3.2 Labour market

Labour demand, or employment, N_t , depends on the demand for goods and services (Keynes, 1937), i.e. aggregate demand, and labour productivity,

$$N_t = \frac{y_t}{y_{n,t}}, \quad (13)$$

where $y_{n,t}$ denotes labour productivity, measured in real GDP per labour (Reati, 2001), which follows the Kaldor-Verdoorn Law,

$$\Delta \ln y_{n,t} = y_{n1} \Delta \ln y_{n,t-1} + y_{n2} \Delta \ln y_t + y_{n3} [\ln y_{n,t-1} - y_{n4} - y_{n5} \ln y_{n,t-2} - y_{n6}(t-1) - y_{n7} \ln y_{t-1}], \quad (14)$$

where $0 < y_{n1} < 1$ denotes the short-run persistence of labour productivity, $y_{n2} > 0$ captures the short-run Kaldor-Verdoorn effect, $-1 < y_{n3} < 0$ denotes the long-run correction of labour productivity, y_{n4} denotes the intercept of the long-run equation of labour productivity in logarithm, $0 < y_{n5} < 1$ is the long-run persistence of labour productivity, $y_{n6} > 0$ captures exogenous labour productivity growth, and $y_{n7} > 0$ captures the long-run Kaldor-Verdoorn effect.

The share of labour force depends on the labour market condition; the higher the real wage, the more they are willing to enter the labour market; the higher the unemployment rate, the less the opportunity for the unemployed to find a job, and the less they are willing to enter the labour market,

$$\Delta \frac{LF_t}{POP_t} = lf_0 + lf_1 \Delta \ln \frac{w_t}{P_{c,t}} + lf_2 u_t, \quad (15)$$

where LF_t denotes labour force, POP_t denotes population, assumed exogenous, w_t denotes the nominal wage, $u_t = 1 - \frac{N_t}{LF_t}$ denotes the unemployment rate, $lf_0 > 0$ denotes the exogenous change of the labour force share, $lf_1 > 0$ is the sensitivity of the change of labour force share to the real wage growth, and $lf_2 < 0$ is the sensitivity of the change of labour share to the unemployment rate.

The nominal wage, adjusts to CPI and depends on labour productivity and unemployment (Hein, 2006),

$$\Delta \ln w_t = w_1 \Delta \ln P_{c,t} + w_2 \Delta \ln \frac{y_t}{N_t} + w_3 \left(\ln w_{t-1} - w_4 - w_5 \ln P_{c,t-1} - w_6 u_{t-1} - w_7 \ln \frac{y_{t-1}}{N_{t-1}} \right), \quad (16)$$

where $w_1 > 0$ denotes the short-run elasticity of nominal wage to CPI, $w_2 > 0$ is the short-run elasticity of nominal wage to labour productivity, $-1 < w_3 < 0$ is the long-run correction parameter of nominal wage, w_4 is the nominal wage level in logarithm with full employment, CPI equals 1 and labour productivity equals 1 rmb per labour, $w_5 > 0$ is the long-run elasticity of nominal wage to CPI, $w_6 < 0$ denotes the sensitivity of nominal wage to unemployment and $w_7 > 0$ denotes the long-run elasticity of nominal wage to labour productivity. The unemployment rate has a negative effect on the nominal wages because it decreases the probability of finding new jobs for workers, and consequently, the value of their outside options is reduced. Conversely, firms have a higher probability of filling their vacancy under a higher unemployment labour market. In summary, workers are worse off, and firms are better off in the wage bargaining process as the unemployment rate increases (Pissarides, 2000).

4.3.3 Households

Household consumption per capita depends on their disposable income per capita deflated by consumption good price, $\frac{YD_{h,t}}{P_{c,t}POP_t}$, i.e. income effect,

$$\Delta \ln \frac{c_{h,t}}{POP_t} = c_1 \Delta \ln \frac{YD_{h,t}}{P_{c,t}POP_t}, \quad (17)$$

where $c_1 > 0$ captures the income effect of household consumption per capita.

Housing demand depends on the population (Zezza, 2008). For simplicity, we assume a constant household non-financial asset acquisitions in volume per capita, $\frac{i_{h,t}}{POP_t} = \gamma_{i_h}$.

Households borrow loans, mainly mortgages, to buy houses. They borrow more when the real rate of interest received from other savings increases or the real housing price increases and less when the borrowing cost increases,

$$\frac{\Delta L_{h,t}}{YD_{h,t}} = l_{h0} + l_{h1}(r_{d,t} - \pi_{y,t}) + l_{h2}(r_{l_{h,t}} - \pi_{y,t}) + l_{h3}(\Delta \ln P_{k_{h,t}} - \pi_{y,t}), \quad (18)$$

where $\pi_{y,t} = \frac{\Delta P_{y,t}}{P_{y,t-1}}$ denotes the GDP deflator inflation, l_{h0} denotes the preference for loan borrowing, $l_{h1} > 0$ denotes the sensitivity of household loans borrowing ratio to the real deposit rate, $l_{h2} < 0$ denotes the sensitivity of household loans borrowing ratio to the real rate of interest paid by households, and $l_{h3} > 0$ is the sensitivity of households loan borrowing to real housing price growth.

Households' deposit savings close their budget constraint,

$$\Delta D_t = YD_{h,t} - C_{h,t} - I_{h,t} - EO_{h,t} + \Delta L_{h,t} - \Delta Z_{h,t}, \quad (19)$$

where $EO_{h,t}$ denotes household errors and omissions, $\Delta Z_{h,t}$ denotes changes in household other accounts payable/receivable.

4.3.4 Firms

Firm gross non-financial asset formations is driven by the net profit (Kaleckian),

$$\frac{\Delta k_{f,t}}{k_{f,t-1}} = \beta_1 \frac{\Delta k_{f,t-1}}{k_{f,t-2}} + \beta_2 \frac{\Pi_{t-1} - r_{l_{f,t}} L_{f,t-1}}{P_{k,t} k_{f,t-1}}, \quad (20)$$

where Π_{t-1} denotes gross operating surplus, $0 < \beta_1 < 1$ denotes the persistence of firm non-financial asset formation rate, $\beta_2 > 0$ is the sensitivity of firm non-financial asset formation rate to the net profit rate.

Firms borrow loans to finance their financial constraint,

$$\Delta L_{f,t} = \Delta Z_{f,t} - NFI_{f,t}, \quad (21)$$

where $\Delta Z_{f,t}$ denotes changes in firm other accounts payable/receivable and $NFI_{f,t}$ denotes firm net financial investment.

4.3.5 Banks

For simplicity, we assume bank non-financial asset formations in volume proportional to real GDP,

$$i_{b,t} = \gamma_{i_b} y_t. \quad (22)$$

The central bank adjusts the policy rate following a Taylor rule,

$$r_{cb,t} = \rho_0 + \rho_1 r_{cb,t-1} + \rho_2 \pi_t, \quad (23)$$

where $\pi_t = \frac{\Delta P_{c,t}}{P_{c,t-1}}$ denotes CPI inflation, $\rho_0 > 0$ is the lower bound of the policy rate, $0 < \rho_1 < 1$ denotes the persistence of the policy rate, and $\rho_2 > 0$ is the sensitivity of the policy rate to CPI inflation.

The deposit rate follows the policy rate,

$$\Delta r_{d,t} = r_{d1} \Delta r_{cb,t}, \quad (24)$$

where $r_{d1} > 0$ denotes the sensitivity of deposit rate change to policy rate change.

Banks ask for spreads when setting the lending rate to firms and households,

$$r_{l_f,t} = r_{d,t} + \text{spread}_f, \quad (25)$$

$$r_{l_h,t} = r_{d,t} + \text{spread}_h. \quad (26)$$

Banks are fully state-owned. Bank non-listed shares in value close its balance sheet so that bank net worth are fully transferred to governments,

$$E_{b,t} = K_{b,t} + G_t - D_t + B_t + L_t + Z_{b,t}, \quad (27)$$

where $K_{b,t}$ denotes bank non-financial assets in value, G_t denotes international reserves, D_t denotes household deposits, B_t denotes government bonds in value, $L_t = L_{f,t} + L_{h,t}$ denotes total loans, and $Z_{b,t}$ denotes bank other accounts payable/receivable.

We assume bank finance their gross non-financial asset formations in value by governments in the form of equities,

$$\Delta E_{b,t} = I_{b,t}. \quad (28)$$

Consequently, the revaluation effect of bank non-listed shares are only results from the revaluation of bank assets and liabilities, i.e. non-financial assets and government bonds.³

4.3.6 Governments

For simplicity, we assume government consumption in volume and gross asset formations in volume are proportional to real GDP,

$$c_{g,t} = \gamma_{c_g} y_t, \quad (29)$$

$$i_{g,t} = \gamma_{i_g} y_t. \quad (30)$$

The government bond yield follows the policy rate,

$$\Delta r_{b,t} = r_{b1} \Delta r_{cb,t}, \quad (31)$$

where r_{b1} denotes the sensitivity of government bond yield change to policy rate change.

Governments issue bonds to finance fiscal constraint,

$$\Delta B_{g,t} = \Delta E_{b,t} + \Delta Z_{g,t} - NFI_{g,t}, \quad (32)$$

where $\Delta Z_{g,t}$ denotes changes in government other accounts payable/receivable and $NFI_{g,t}$ denotes government net financial investment.

4.3.7 The rest of the world

The nominal exchange rate follows an imperfect uncovered-interest parity,

$$\Delta \ln xr_t = xr_1 \ln \frac{1 + r_{cb,t} - rp}{1 + ffr_t}, \quad (33)$$

where $0 < xr_1 < 1$ is the imperfection of interest parity caused by capital controls, $rp > 0$ denotes the risk premium of domestic currency cause by currency hierarchy, ffr_t denotes the federal funds rate.

The federal funds rate and foreign GDP (nominated in US dollar), $Y_{r,t}$, are exogenous in the model.

Exports depend on foreign demand converted into domestic currency and deflated by export price, $\frac{Y_{r,t}}{P_{x,t}xr_t}$ (income effect), and the price ratio between export price and foreign price converted in domestic currency, $\frac{P_{x,t}xr_t}{P_{r,t}}$ (substitution effect),

$$\Delta \ln x_t = x_1 \Delta \ln \frac{Y_{r,t}}{P_{x,t}xr_t} + x_2 \Delta \ln \frac{P_{x,t}xr_t}{P_{r,t}}, \quad (34)$$

where $x_1 > 0$ captures the income effect of export demand, x_2 captures the substitution effect of export demand.⁴

³For simplicity, we assume 0 revaluation effect in international reserves.

⁴When $x_2 < 0$, there's a substitution effect between exports and foreign goods. And, when $x_2 > 0$, there's a complement effect between exports and foreign goods.

Similarly imports depend on domestic demand deflated by import price, $\frac{Y_t}{P_{m,t}}$ (income effect), and the price ratio between import price and domestic price, $\frac{P_{m,t}}{P_{y,t}}$ (substitution effect),

$$\Delta \ln m_t = m_1 \Delta \ln \frac{Y_t}{P_{m,t}} + m_2 \Delta \ln \frac{P_{m,t}}{P_{y,t}}, \quad (35)$$

where $m_1 > 0$ captures the income effect of import demand, m_2 captures the substitution effect of import demand.

Changes in international reserves close the balance of payment,

$$\Delta G_t = \Delta Z_{r,t} + NFI_{r,t}, \quad (36)$$

where $\Delta Z_{r,t}$ denotes changes in RoW other accounts payable/receivable and $NFI_{r,t}$ denotes RoW net financial investment.

5 Data and parameters

Our dataset covers a range of the years 1992 to 2022. The economy balance sheets, e.g., non-financial assets and financial assets and liabilities, are obtained from *China's National Balance Sheet 1978-2022* (Y. Li et al., 2015 and Piketty et al., 2019). Transaction data are obtained from National Bureau of Statistics (NBS).

The GDP deflator is obtained from World Development Indicators. Other price variables are obtained or estimated from NBS. The nominal effective exchange rate and Central Bank policy rate, specified with the interbank rate, are obtained from the International Financial Statistics (IFS) of the IMF. The federal funds rate is obtained from the Federal Reserve Economic Data (FRED). The deposit rate, lending rate, unemployment rate, employment and population are obtained from World Bank. The foreign nominal GDP is the world's nominal GDP subtracts China's nominal GDP, based on data from the IMF. The nominal wage is calculated by the wage bill payment over employment. Errors and omissions are calculated based on the accounting equations to solve the mismatch between the physical transaction account and financial transaction account.

Parameters in the behaviour equations are estimated by running OLS regressions with the Durbin-Watson test to ensure they do not reject the homoskedasticity hypothesis (Savin and White, 1977 and Farebrother, 1980). Moreover, we run Augmented Dickey-Fuller (ADF) tests on the residuals to ensure co-integrations between the variables (Engle & Granger, 1987).

6 Simulations

We run a business as usual (BAU) scenario as a baseline from 2017 to 2031 with the population forecast from World Bank, foreign price and RoW nominal GDP forecast from the IMF for the period of 2026 to 2031. We compare our baseline scenario with historical data to show the performance of our model in representing the Chinese economy. In addition, we evaluate the sensitivity of bird footprint and real GDP to a 1% temporary increase in household consumption in volume, firm non-financial asset accumulation rate, and exports in volume, separately, in 2027.

To have a better look, we report the simulation result both in levels and in percentage deviation to the BAU scenario (Figure 2). The black line denotes the BAU scenario. The blue line denotes the consumption shock scenario. The red line denotes the firm investment shock scenario. The purple line denotes the export shock scenario. The response of real GDP and bird footprint are almost 1:1 linearly correlated. It is obvious to see that a shock to firm non-financial asset accumulation rate has a largest impact to bird footprint and the economy, but it should be noted that a shock on firm non-financial asset accumulation rate is much larger than a shock to consumption and export since it depends on the level of the stock. We can see that bird footprint and real GDP increase by 4% in 2027 after a firm investment shock, but diminish over time. Household consumption shows a small increase in the short run and increase slightly overtime, whereas, the effect of an export shock increases gradually overtime. The effect of the three shocks converge to around 1% percent in the long run (Figure 2b and 2d).

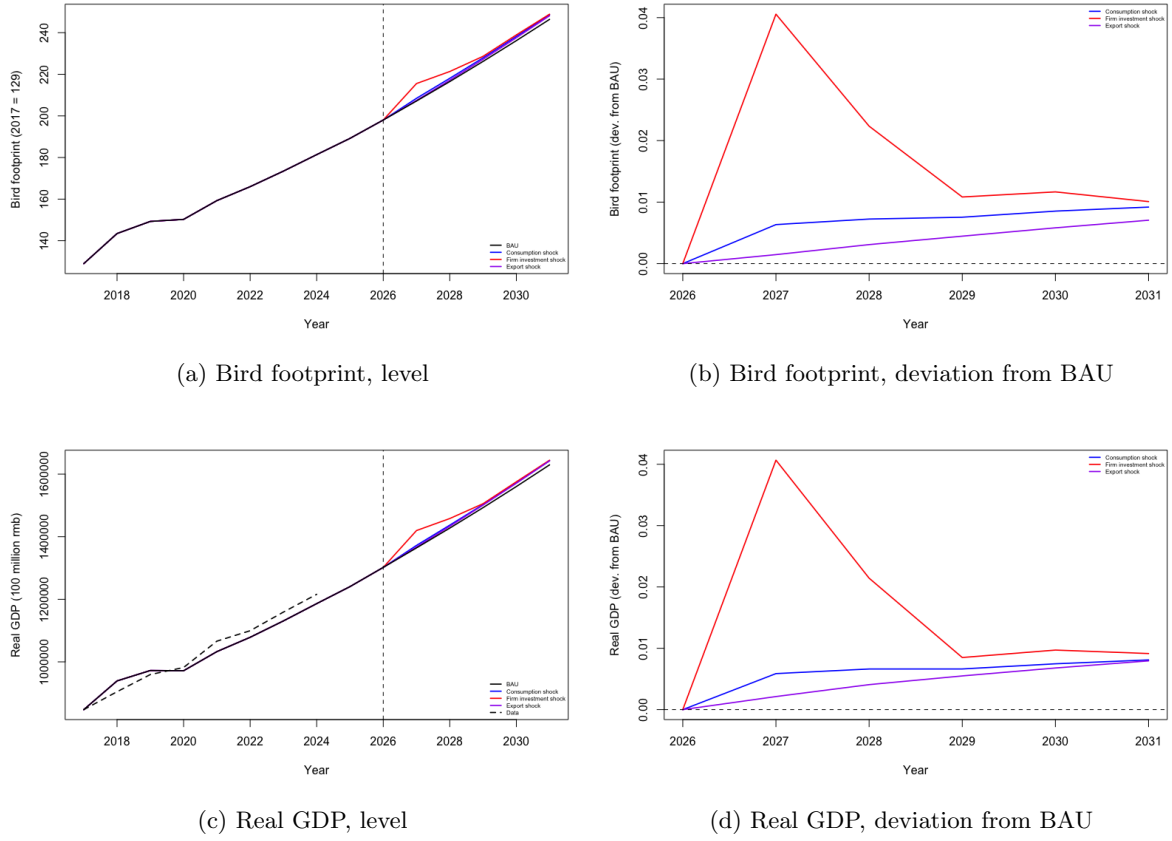


Figure 2: BAU and sensitivity test

Figure 3 shows the bird footprint by industry in the BAU and responses to the three demand shocks. The green line denotes the bird footprint of agriculture, hunting, forestry, logging and related services. The orange line denotes the bird footprint of manufacturing. The brown line denotes the bird footprint of transport, storage, and postal services. Bird footprint is mainly driven by agriculture, hunting, forestry, logging and related services, followed by transport, storage, and postal services (Figure 3a). A household consumption shock drives the bird footprint of agriculture, hunting, forestry, logging and related services the most (Figure 3b). Whereas, manufacturing and transport, storage, and postal services are the main drivers of bird footprint in response to a firm investment and export shock (Figure 3c and 3d)

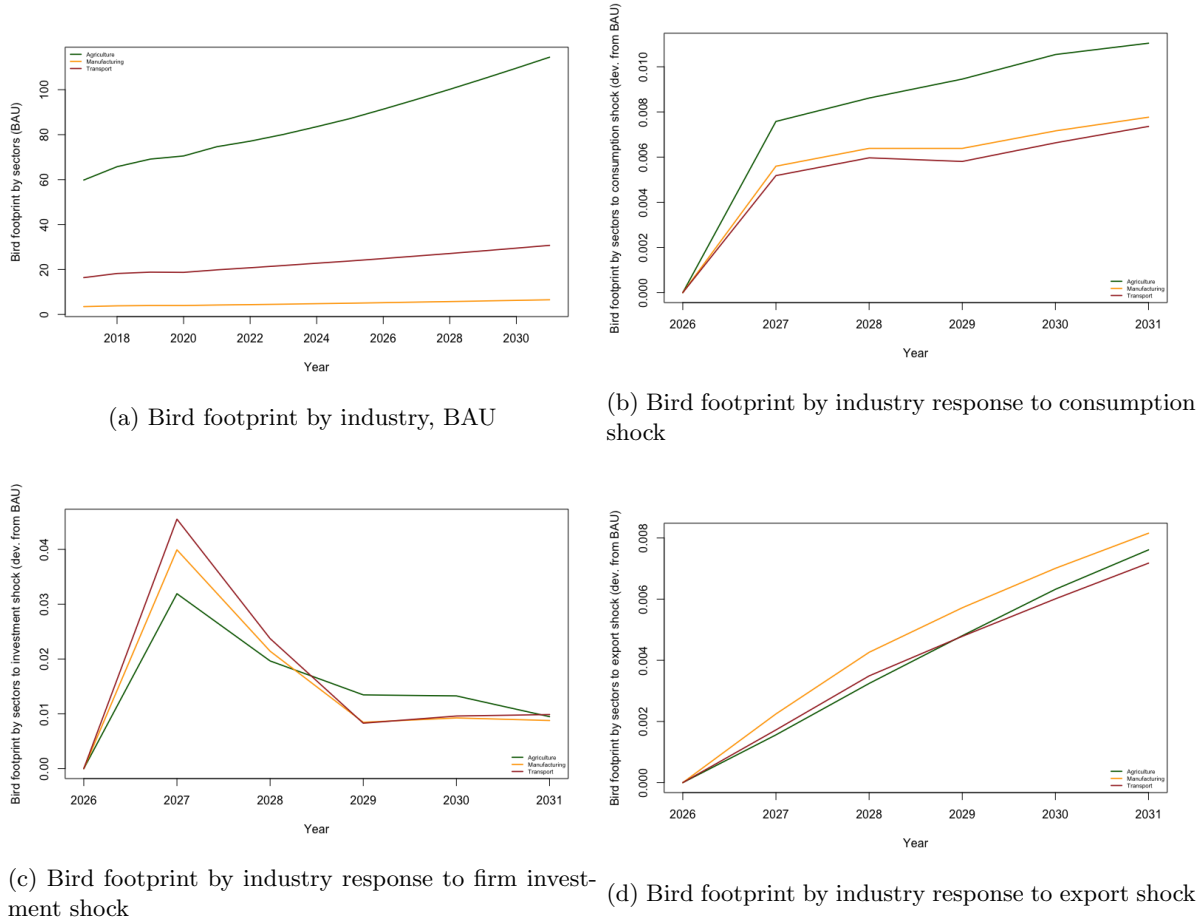


Figure 3: Bird footprint by industry

Figure 4 shows the bird footprint response to the three demand shocks by region in 2027 and 2031 in percentage deviation from BAU. It can be observed that household consumption increase bird footprint in the South and South west provinces, mainly in Guizhou, Gansu, Chongqing and Sichuan, with more than 0.7% in 2027, and amplify to around 1% in 2031. Firm investment increase bird footprint more evenly across provinces than the other two shocks, slightly more in those industrial provinces, such as, Jilin, Hebei, Anhui and Inner-Mongolia etc., with around 4.5% increase in 2017, and diminish to around 1% increase in 2031. Exports increase the bird footprint in the East and South provinces, with more than 0.2% in 2027 and around 0.8% in 2031.

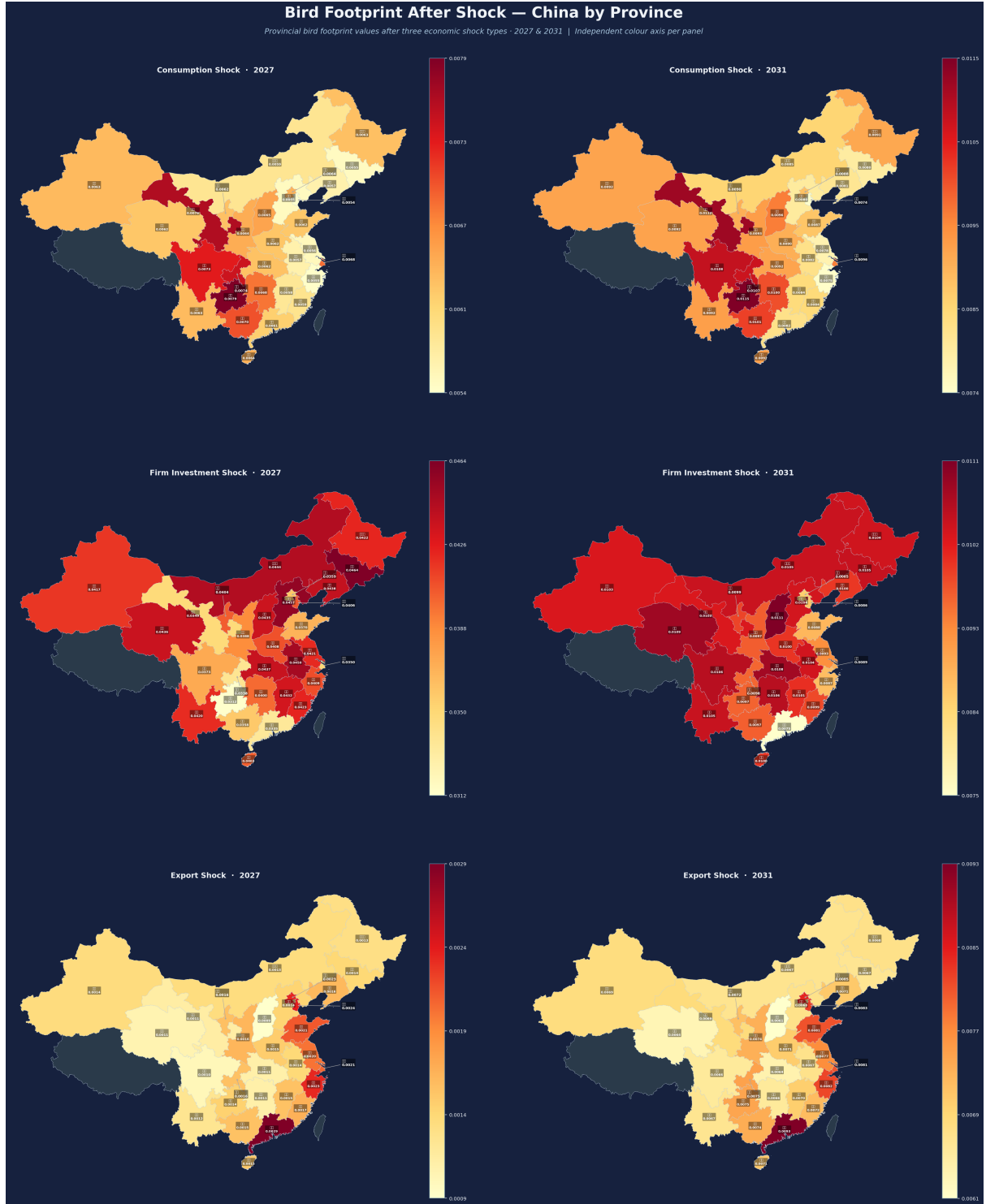


Figure 4: Bird footprint by province in 2027 and 2031 (deviation from BAU)

7 Conclusion and remark

This paper develops a MRIO-SFC model for China to analyze the linkage between bird diversity and macroeconomy of China and provide macro policy implications. At the current stage, we run the model with a BAU scenario and implement three aggregate demand shock upon of that, a 1% increase in household consumption, 1% increase in firm non-financial asset accumulation rate, and 1% increase in exports. It shows that bird footprint and real GDP are more sensible to firm non-financial asset accumulation rate in the short run, both with an elasticity around 4. In the long run, the effect of

the three shocks converge to around 1%. Regarding to the industrial structure, household consumption mainly impulse the bird footprint contribution of the agricultural sectors, while firm investment and exports mainly impulse the contribution of manufacturing and transport sectors. Regarding spatial distributions, a household consumption shock increases the bird footprint of the South West and South provinces significantly. An investment shock increases bird footprint across all the provinces, leading by industrial provinces. And an export shock mainly increases the bird footprint of the South and East provinces.

Several limitations of this paper should be acknowledged. We cannot quantify the feedback effect of the threaten and near-threaten species to the economy, i.e. their economic value, nor we can quantify the interdependence of different species through the biodiversity footprint. These limitations may all undervalue the importance of species to human society and the impact of the economy to the species. Two further limitations point to where this work should go next. First, our model accounts for the bird footprint of domestic production only. We derive domestic output by subtracting imports, but this subtraction operates in value terms alone. It removes the economic contribution of imported goods without accounting for the biodiversity loss generated in producing them abroad. The two magnitudes are unrelated. Cheap imported inputs subtract little economic value, while the ecological pressure behind their extraction may be severe. Transport is a clear case. The footprint of the rare earth mining carried out overseas to supply the batteries on which Chinese transport increasingly depends is absent from our accounts. It cannot be recovered from import values, since price is not a measure of embodied biodiversity threat. A consumption based accounting that traces these international supply chains through foreign threat coefficients would be needed to capture it. Second, our threat coefficients and input-output structure are fixed to 2017. China’s industrial composition, trade patterns, and energy mix have changed considerably since then, and holding these coefficients constant understates that transformation. Updated and, where possible, time varying data would address this. Rather than a final account, we intend this model as a foundation for a new line of work on biodiversity and the macroeconomy. Future research can extend the boundary to footprints generated abroad, incorporate mining and other upstream activities located outside China, and draw on more recent data covering a wider set of species.

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Appendix

MRIO

Household consumption in volume by industry and region,

$$c_{h,i,r,t} = \gamma_{c_{h,i,r}} c_{h,t}. \quad (37)$$

Government consumption in volume by industry and region,

$$c_{g,i,r,t} = \gamma_{c_{g,i,r}} c_{g,t}. \quad (38)$$

Non-financial asset formations in volume by industry and region,

$$i_{i,r,t} = \gamma_{i_{i,r}} (i_{f,t} + i_{b,t} + i_{g,t}). \quad (39)$$

Exports in volume by industry and region,

$$x_{i,r,t} = \gamma_{x_{i,r}} x_t. \quad (40)$$

Final imports in volume by industry and region,

$$m_{i,r,t} = \gamma_{m_{i,r}} m_t. \quad (41)$$