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Accelerated economic recovery in countries powered by renewables

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ABSTRACT

The human economy is in effect a subsystem of the biosphere. Ecosystems provide natural resources that are fundamental to both societal well-being and economic performance. Here, we show how recovery of national economies from systemic crises can be moderated by the natural resources used to power them. By examining data from 133 systemic economic crisis events in 98 countries over 40 years, we found that countries relying on a broad range of electricity sources experienced extended recovery times from crises, though that effect was tempered somewhat when the relative contribution of those sources was increasingly balanced. However, the best predictor of economic recovery was the extent of reliance on renewable energy—we found that economic recovery tends to be swiftest in countries powered primarily by renewable energy sources. These findings have profound implications for global energy policy and reveal the need to consider both the composition and diversity of energy sources in models of economic resilience.

1. Introduction

Energy underpins all economic activity. The present globalised economy is powered primarily by fossil fuels such as coal, oil and gas (Goldemberg, 2006; International Energy Agency, 2020), which are generally characterized as "enabling" resources, comprising concentrated sources of high quality energy that underpin the production and supply of almost all goods that drive modern civilization, including food and electricity (Fantazzini et al., 2011). About half of the changes in economic growth, measured as Gross Domestic Product (GDP), since 1970 can be explained solely by patterns of oil consumption (Murphy and Hall, 2011), while fluctuations in the accessibility and cost of fossil fuels have been implicated as triggers of economic instability and recessions (Shafiee and Topal, 2010; Hamilton, 2011; Murphy and Hall, 2011). In spite of its fundamental role in supporting economic activity and its implicit links with economic stability, however, energy—that is, the particulars of its production and consumption—remains a generally underappreciated driver of economic dynamics (Kümmel, 2011; Kümmel and Lindenberger, 2014). Moreover, its potential for shaping the responses of economies to unforeseen crises or "shocks" is largely unknown.

Shocks to the economic system, such as international economic crises, are generally characterized primarily as financial crises (Schweitzer et al., 2009; Battiston et al., 2016b). This view ignores, however, the fundamental link between the dynamics of economic networks and their reliance upon the energy and material resources provided by ecosystems (Armsworth and Roughgarden, 2003; Costanza et al., 2014a). One fundamental property of networks that is known to be a key determinant of their stability—that is, their dynamics and how they respond to perturbations (Donohue et al., 2016)—is the number of interacting nodes within the system (May, 1973; Allesina and Tang, 2012; Battiston et al., 2016a; Meena et al., 2023). In ecological networks, for example, the nature of the relationship between the number of species living in an ecosystem and the stability of the system has received particular scrutiny, comprising a central focus of the field for decades (Elton, 1958; May, 1973; McCann, 2000; Tilman et al., 2006; Hautier et al., 2014;

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White et al., 2020). There is now widespread theoretical (Yachi and Loreau, 1999; Allesina and Tang, 2012) and empirical (Tilman et al., 2006; Isbell et al., 2015) evidence to show that greater species richness tends to enhance the stability of ecosystems and buffer them against declines in their overall functioning after perturbations (though this pattern is not universal; see, for example, Jacquet et al., 2016; Landi et al., 2018; Pennekamp et al., 2018). This pattern arises because, in a fluctuating world, different species respond to environmental changes in different ways, and the presence of many species increases the likelihood that some will maintain or help recover the overall functioning of the system even if others fail (Yachi and Loreau, 1999; Ross et al., 2021).

The relationship between diversity and stability has also been explored in other network types. In food distribution networks, for example, both theoretical (Nyström et al., 2019; Renard and Tilman, 2019) and empirical (Gomez et al., 2021) analyses have found that greater diversity of food supply chains reduces the risk of food shock to human populations. A particularly striking application of the relationship in economic systems is Mean-Variance Portfolio Theory, where the diversification of investment portfolios is used as a risk management instrument to dampen the overall volatility of investments (Markowitz, 1952). However, as both network structure and the nature and strength of interactions between nodes play critical roles in determining stability (Allesina and Tang, 2012; Meena et al., 2023), greater diversity is not universally stabilizing. Indeed, recent research indicates that diversification of financial networks may not be optimal for stability (Stiglitz, 2010; Battiston et al., 2012) and may even be inherently destabilizing (Bardoscia et al., 2017). Moreover, given the inherent multidimensionality of both diversity and stability across all network types (Donohue et al., 2016; Kéfi et al., 2019), the strength and nature of relationships between them also depend fundamentally upon the focal dimensions being analysed (Pennekamp et al., 2018; White et al., 2020).

Here, we combine a general theoretical model and empirical analyses of real-world data to explore whether, and how, the recovery of national economies from shocks might be moderated by the energy sources that power them. First, we draw from ecological network theory (May, 1973; Gellner and McCann, 2016) as a means to understand in a very general way (using random matrix theory) how the use of natural resources can moderate a country's GDP response to a shock to the economic system (Fig. 1). We then use real-world economic data collated from 133 systemic economic crisis events in 98 countries over 40 years, covering a diverse range of economies, societies and economic crises, to examine empirically how the diversity and composition of energy sources used in a country relates to the rate of its recovery from systemic economic crises.

2. Methods

2.1. Mathematical model

We generated a mathematical matrix model that makes realistic assumptions about how natural resource sectors (that is, economic sectors that are based directly upon natural resources such as, for example, oil, water, gas, etc.) interact to produce GDP (Fig. 1). We used the model to explore how the number of natural resource sectors underpinning an economy influences its rate of recovery following an unforeseen external "shock". The use of random matrices comprises a powerful approach for studying the stability of large networks of interacting nodes (Gardner and Ashby, 1970; May, 1972; Edelman and Rao, 2005). The approach requires that the topic under study can be represented as a matrix of interactions, or network, where each of the rows/columns represent the nodes of the network, and the entries correspond to the strength of the modelled interactions. As the exact strength of the interactions is rarely known, random distributions are often used for the matrix elements (that is, interaction strengths). Once the elements are sampled randomly, the dominant eigenvalue (λ_{max})—a measure of the stability of the network—can be calculated. The sign of the real part of the dominant eigenvalue ($Re\lambda_{max}$) determines whether the system returns to equilibrium or not following a perturbation, while the absolute value of the real part of the (negative) eigenvalue provides an approximation to the rate of the return to equilibrium [the return time can be

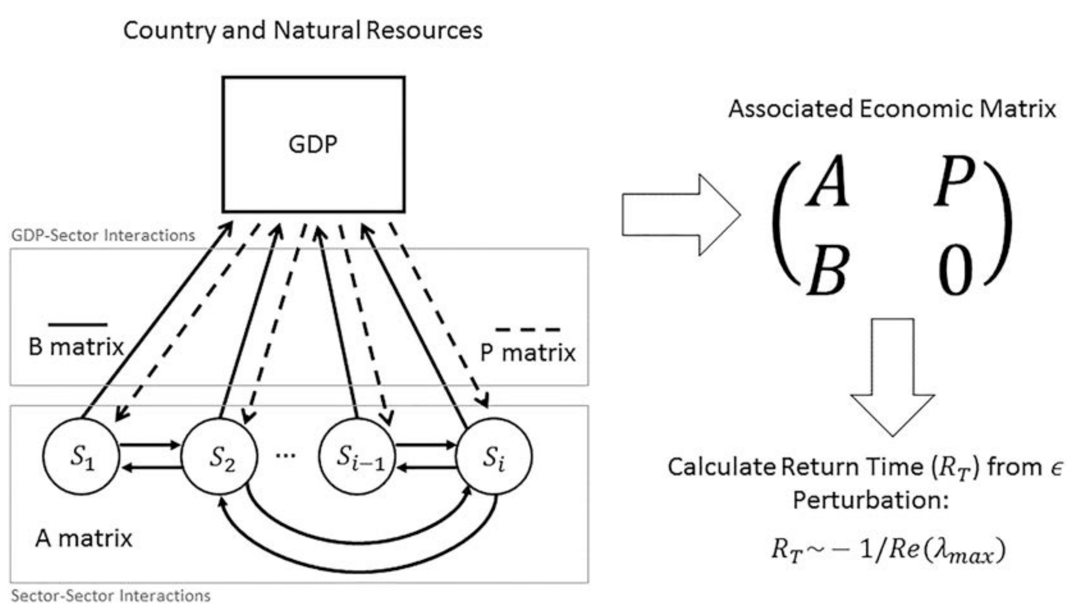

Fig. 1. Simple macro-economic model of the dynamic interactions between natural resources and GDP. We model the economic network as a collection of positive and negative feedbacks between GDP growth and natural resource sectors [S_i; that is, economic sectors that are based directly upon natural resources (e.g. oil, water, gas, etc.)] coupled to inter-sector interactions (that is, sector competition, cooperation, or both). Positive feedbacks, the contribution of a sector to GDP, are encoded in the B matrix. Negative feedbacks, the associated removal of the sector product, are encoded into the P matrix (though these feedbacks can sometimes be positive to capture the possibility that, over short time spans, increasing GDP can lead to positive impacts on sector growth). The nature of the interaction between resource sectors is described in the A matrix, which describes all pairwise interactions between every natural resource sector in the economy. We then use this model to examine how the rate of recovery [that is, return time R_T, the reciprocal of the absolute value of the real part of the (negative) eigenvalue $Re\lambda_{\max}$] from a "shock" to the economic system is affected by the number of interacting natural resource sectors in the network (see *Methods* for a full description of our model).

approximated as $1/(|Re\lambda_{max}|)$].

Our modelling approach (Fig. 1) turned the financial ecosystem (sensu May et al., 2008; Haldane and May, 2011) of a country's GDP into a country matrix. The matrix is closely related to the qualitative stability analysis of economists (Samuelson, 1947). For simplicity, we assume that a country has a GDP equilibrium (G^*), and that any given country has access to invest in a diverse array (n) of natural resources (S_i; e.g., oil, solar, wind, etc.). We further assume that each of these natural resources supplies goods (energy) at some rate and these supplies are, in turn, consumed at some rate by society, ultimately producing GDP at some rate for a given country. If we consider instantaneous linear rates describing all pairwise interactions between state variables (that is, all the S_i's and G), then Fig. 1 represents a set of linear ordinary differential equations that is identical to the linear form of consumer-resource models used in ecology (Murdoch et al., 2013). This mathematical approach allows us to represent the dynamic response of a very complex system to a small perturbation off the equilibrium. It allows us to do this because the dynamics of a small ε-perturbation off the equilibrium necessarily means that the dynamics are dominated by linear terms, even if the system under study is actually governed by strong nonlinearities. As a result, this relatively simple approach offers an elegant way to garner insight into how extremely complex systems can be expected to respond to shocks.

For the model, we build a block random matrix of the form:

$$\begin{pmatrix} A & P \\ B & 0 \end{pmatrix}$$

where A is a $n \times n$ matrix measuring the competition (negative elements) or cooperation (positive elements) between the n natural resource sectors. The P matrix has shape $n \times 1$, encoding the effect of changes in the GDP on the respective (row) sector. Finally, the B matrix is a $1 \times n$ list of entries describing the positive contribution of changes to GDP on each resource sector (Fig. 1).

The network of interactions between the resource sectors for the given economy is described in the A matrix, which can be thought of as having off-diagonal pairs (a_{ij}, a_{ji}), such that the sign of the each of the elements determines the type of interaction [(−, −) for competition, and (+, +) for cooperation], and the magnitude of the element determines the strength of the interaction. As not all natural resource sectors in an economy need to interact, we introduce (0, 0) elements in the A matrix to represent a missing interaction between a pair of sectors. The number of interactions that occur in a network expressed as a proportion of all possible linkages is commonly called the connectance in ecological systems, and will be between 0 and 1, where 0 means none of the sectors interact and the network is completely disconnected, whereas 1 means all sectors interact [and there are no (0, 0) off-diagonal pairs in the A matrix].

To generate the economic network matrix with natural resource sector diversity n, we create the three random matrices described above (B, P, A) using the following procedure: first, randomly generate n elements from a Uniform distribution between (0, 1) and assign them to row vector B; then, generate n elements randomly from a Uniform distribution between (−0.2, 0.1) and assign them to column vector P. We allow the role of changes in GDP on the growth of the natural resource sectors to be negative or positive to capture the possibility that, over short time spans, increasing GDP in a country can lead to positive impacts on sector growth if things like worker productivity, technological/research-development etc. were to increase, though we set the parameters such that, on average, increases in GDP will largely use up the growth in each of the natural resource sectors (negative entries in the P matrix).

Finally, to generate interaction matrix A, we modelled three scenarios: 1) pure competition, (−, −) off-diagonal entries; 2) pure cooperation, (+, +) off-diagonal entries; and 3) a mixture of (−, −) and (+, +) off-diagonal pairs. For each of the three scenarios, we further looked at parameterizations that had low/weak mean interaction strength, and higher/strong mean interaction strength. For pure competition with weak interactions, we drew random samples from a Uniform distribution between (−0.10, 0). For stronger pure competition, we drew the elements from a Uniform distribution between (−0.4, 0). For weak pure cooperation, we drew random samples from a Uniform distribution between (0, 0.05). For stronger cooperation, we drew random samples from a Uniform distribution between (0, 0.2). The Uniform distribution bounds for competition, cooperation, and mixed competition and cooperation were derived using a numerical root solver (bisection) to calculate when the average real part of the dominant eigenvalue was 0 for when the sector diversity was equal to 20. In this way, we are allowing for the greatest equilibrium behaviour over the range of sector diversity we are examining. This value would give our "strong" interval for the interaction, so that we would be sampling over Uniform(0, strong), and Uniform(0, strong/4) for weak. In this way, we use a consistent manner to select the parameter ranges, allowing the maximum equilibrium width given the underlying parameters (that is, number of sectors, effect of GDP, and connectance). Importantly, we compare weak versus strong interactions through a change in the width of the parameter interval, not the mean, for simplicity. The uneven interval widths occur because the relationship to stability for (−, −) interactions versus (+, +) interactions is not linear, and (+, +) feedbacks generically destabilize a system more rapidly than (−, −) (May, 1976).

For all scenarios, we set the connectance to 0.5, though the pattern remains qualitatively similar for different connectance values. As the connectance increases, the strength of mean interaction strengths needed for a stable configuration goes down, as would be expected from general theory (May, 1972; Allesina and Tang, 2015). The last detail for the A matrix is to set the diagonal elements. This measures the effect that a sector's growth has on itself. As this value is often not well understood it is common to set the value to −1 (May, 1972; Allesina and Tang, 2012), which we have followed. In general, so long as the diagonal is relatively tightly distributed, then the exact value will not have a large effect on stability. We verified numerically that solutions with the diagonal elements set from a Uniform distribution between (−1.5–0.5) give qualitatively identical answers, though, as random matrix theory suggests (Allesina and Tang, 2012), the maximum width of the interaction strength distribution is reduced by increasing diagonal variation. That is, the range of parameter values decreases as the diagonal variation increases if we require a stable equilibrium across the sector diversity.

2.2. Data analyses

To complement our general theoretical exploration of how the diversity of natural resources can moderate economic recovery from shocks, we test explicitly whether and how the diversity and composition of energy sources used in real-world national economies relate to the rate of their recovery from systemic economic crises. Because diversity is an aggregate measure combining measures of richness and evenness (Shannon, 1948), we analysed relationships between economic recovery and both the number of electricity sources and the relative evenness of their contributions to the electricity mix separately (Table S3). We measured evenness using Pielou's Evenness Index (Pielou, 1966). Specifically, we examine how the (i) number and (ii) evenness of electricity sources relate to the rate of economic recovery from systemic crises. We focus here only on electricity data for these analyses as data on the relative contribution of electricity sources were available for all countries at the timescales and resolution required for us to examine relationships between the diversity of electricity sources and economic recovery time in the most detailed and consistent manner possible. We then go on to explore (iii) whether there are particular aspects of the composition of the overall energy mix (that is, including, but not limited to, electricity sources) used in countries that relate especially strongly to rates of their economic recovery from shocks.

We quantified the recovery dynamics of national economies that experienced systemic economic crises events using data from the International Monetary Fund (IMF) for the period 1970–2011 (Laeven and Valencia, 2013; 65 crisis events in 53 countries), supplemented with data from 68 countries that experienced systemic crises following the 2008 global financial crisis (Table S1). The 2008 global financial crisis triggered the longest and deepest economic downturn in many countries since the Great Depression (1929 - c. 1939), with evidence of its lasting impacts on potential growth, income inequality, fertility rates and migration (IMF, 2018). A crisis event is defined in the IMF database as an event that meets two conditions: (1) significant signs of financial distress were observed (that is, significant bank runs, losses in the banking system, and/or bank liquidations); and (2) significant policy intervention measures were undertaken in response to losses in the banking system. Policy intervention measures were defined as significant if at least three of the following six measures were used: deposit freezes and/or bank holidays; significant bank nationalisations; bank restructuring gross costs (at least 3% of GDP); extensive liquidity support (5% of deposits and liabilities to non-residents); significant guarantees put in place; or significant asset purchases (at least 5% of GDP). The first year that both criteria were met was considered as the starting year of the crisis event. This screening method avoided the labelling of non-systemic events or the pre-emptive use of policy actions as a systemic crisis.

For every crisis event, we collected data on GDP and the composition of the energy mix that powered national economic production in the starting year of the crisis event. We quantified the recovery time of economies as the length of time required for GDP to return from its lowest point after a crisis to pre-crisis levels (that is, the reciprocal of resilience; Donohue et al., 2016). The GDP data were taken from the International Financial Statistics database of the International Monetary Fund (www.imf.org). They were converted into 2020 US dollars using Purchasing Power Parity rates (PPP) to standardise GDP across different national economies and years. Energy data were taken from the World Bank World Development Indicators (WDI) database, which is based in part on data from the International Energy Agency (see Table S2 for energy variables used in our analyses). We excluded from our analyses countries whose GDP did not fall in response to the global financial crisis of 2008 (25 out of 103 countries in our dataset).

Given that some countries in the dataset experienced more than one crisis in our focal time period (Table S1), we used generalized linear mixed-effects models (GLMM, with gamma errors and an inverse link function) to analyse economic recovery times, using lme4 (Bates et al., 2015). Because the magnitude of economic crises (that is, the relative extent of loss of GDP following the crisis) likely strongly influences the time required for recovery, we also incorporated crisis magnitude as a fixed effect in all models. Country was incorporated as a random factor in all analyses. Our GLMM models took the form:

$$\text{Economic recovery time (years)}_{ij} \sim \text{Gamma}(\mu_{ij})$$

$$\text{E}\left(\text{Economic recovery time (years)}_{ij}\right) = \mu_{ij}$$

$$log(\mu_{ij}) = \alpha + \beta_1\left[\text{Crisis magnitude}_j\right] + \beta_2 X_{ij} + \beta_3\left[\text{Crisis magnitude}_j \times X_{ij}\right] + \text{Country}_i$$

$$\text{Country}_i \sim N(0, \sigma^2)$$

where μ_{ij} is the expected economic recovery time that is fitted by the model, X is the energy/electricity variable of interest; α is the model intercept, β_1, β_2, and β_3 are the model coefficients, and Country_i is the random intercept that follows a normal distribution with zero mean and σ^2 variance. We used Akaike's Information Criterion (AIC) to compare the relative performance of competing models (following Burnham and Anderson, 2004). All analyses were done using R statistical software (version 4.0; R Core Team, 2020).

3. Results

Our mathematical matrix model shows (Fig. 2) that, regardless of the type of interactions between sectors (that is, whether they are

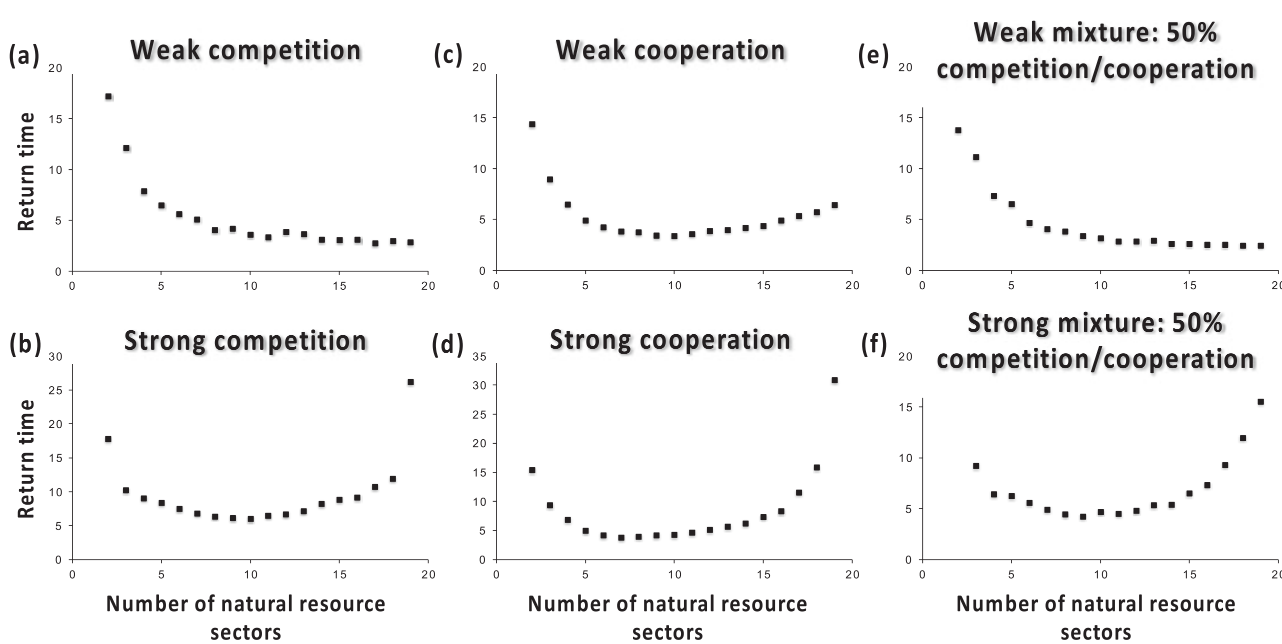

Fig. 2. Our theoretical model predictions of how the number of natural resources contributing to GDP moderates economic stability. Predicted stability response (return time of GDP after a shock) to increasing numbers of natural resource sectors in a country's economy under (a) weak competition (−0.1 maximum mean negative interaction between sectors); (b) strong competition (−0.4); (c) weak cooperation (+0.05 maximum mean positive interaction); (d) strong cooperation (+0.2); and an even mixture of (e) weak and (f) strong competitive and cooperative interactions. Note, even stronger competition or cooperation can yield a strictly decreasing stability response (that is, consistently increasing return times), though such high values presuppose an extremely strong average interaction between sectors.

competitive, cooperative or a mixture of both), return (recovery) time consistently decreases (that is, the network is more stable in the face of a shock) with greater richness of natural resource sectors up to a point, beyond which recovery times then increase as the number of resource sectors increases. The latter pattern of increasing destabilization occurs at lower and lower levels of natural resource richness as the strength of intersectoral interactions increases (the patterns shown on all panels of Fig. 2 are qualitatively similar, and this destabilization occurs at greater numbers of natural resource sectors than shown in Figs. 2(a) and 2 (e)).

This pattern of stabilization followed by destabilization as the number of resource sectors increases occurs as a balance between two offsetting forces: the potential avoidance of shocks to critical network pathways versus increasingly potent interactions between sectors. At low resource sector richness, shocks will have a high likelihood of upsetting the delicate balance between the dominant pathways for the growth of GDP, as there is little potential for any form of risk mitigation from less impacted alternate resource sectors. But, as more sectors contribute to GDP production, shocks will no longer affect every sector to the same degree, allowing for more muted response to shocks. Offsetting the increasingly diverse resource base, as the number of sectors increases, the potential for inter-sector interactions cause the effect of shocks to be magnified, setting up cascades of sector collapses as competitive or cooperative dominance spreads across the network. In summary, our theory indicates that increasing richness of resource sectors can retard or accelerate economic recovery time following shocks, depending upon the strength—but not the nature—of interactions between sectors.

Next, we examined empirical relationships between the recovery rates of 98 real national economies from 133 systemic crisis events and the diversity (that is, both the richness and evenness) of their electricity supply. We found that the time taken for national economies to recover from systemic crises was associated positively with the number of electricity sources (Fig. 3a). Further, this effect strengthened when crises were increasingly large (GLMM for interaction between number of electricity sources and crisis magnitude: $t = -2.51$, $P = 0.012$). This effect was, however, tempered somewhat when countries had more balanced contributions from different resource sectors—we found that faster recovery times from large crises tended to occur in countries with higher evenness in the contributions from their different electricity sources (Fig. 3b; GLMM for interaction between evenness of electricity sources and crisis magnitude: $t = 2.4$, $P = 0.016$; model estimates and diagnostics are shown in, respectively, Table S3 and Fig. S1).

Finally, we explored relationships between the recovery times of real economies from systemic crises and the composition of the overall national energy mix. We found that the best model for predicting economic recovery from energy data included the share of renewable energy in

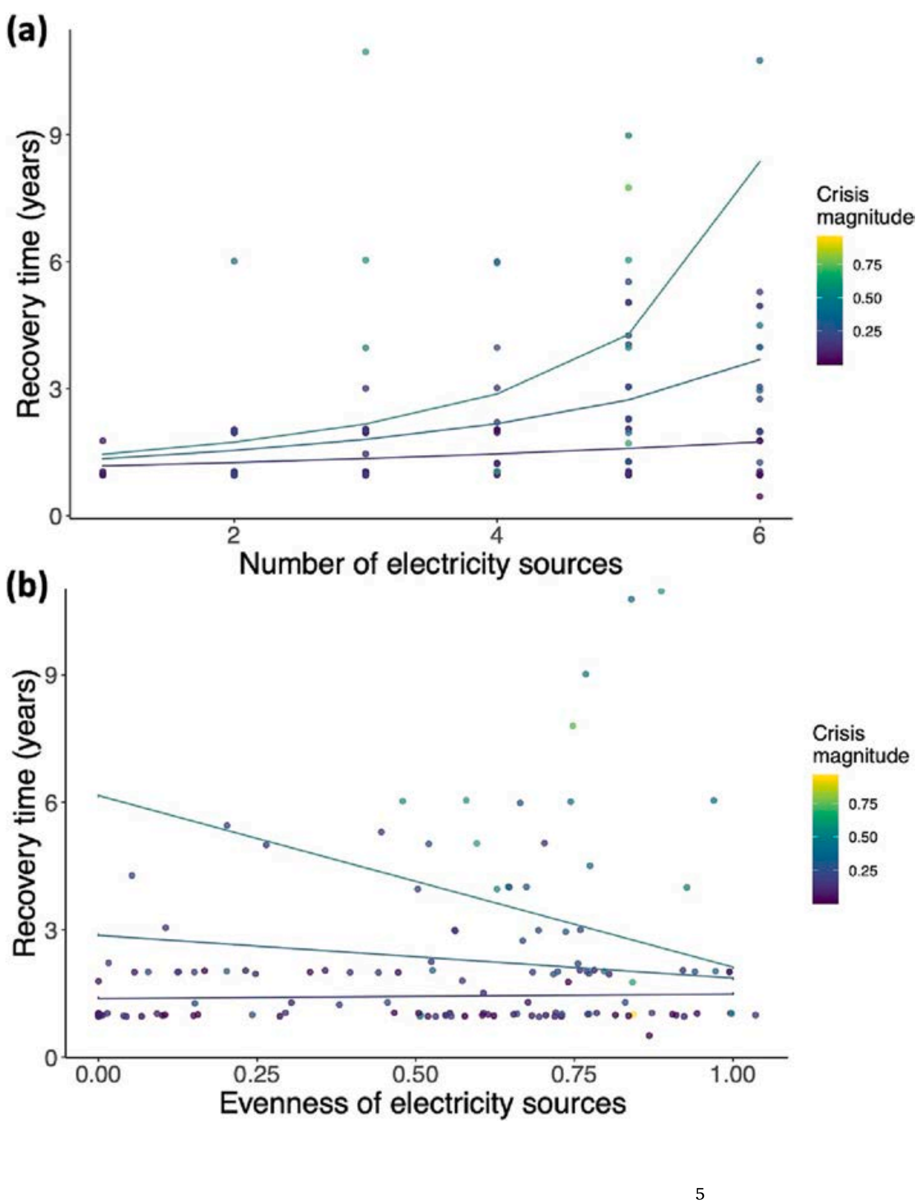

Fig. 3. Empirical relationships between the diversity of electricity sources and the recovery of real national economies from systemic crises. Scatterplots of the time taken for national economies to recover from systemic crises and the (a) number and (b) evenness of electricity sources in the country. Points are for individual crisis events ($n = 133$), coloured by crisis magnitude (that is, the proportional reduction in GDP following the crisis). Lines correspond to GLMM model predictions for crises corresponding to drops of 20%, 40% and 60% of GDP. Model estimates and diagnostics are shown in, respectively, Table S3 and Fig. S1.

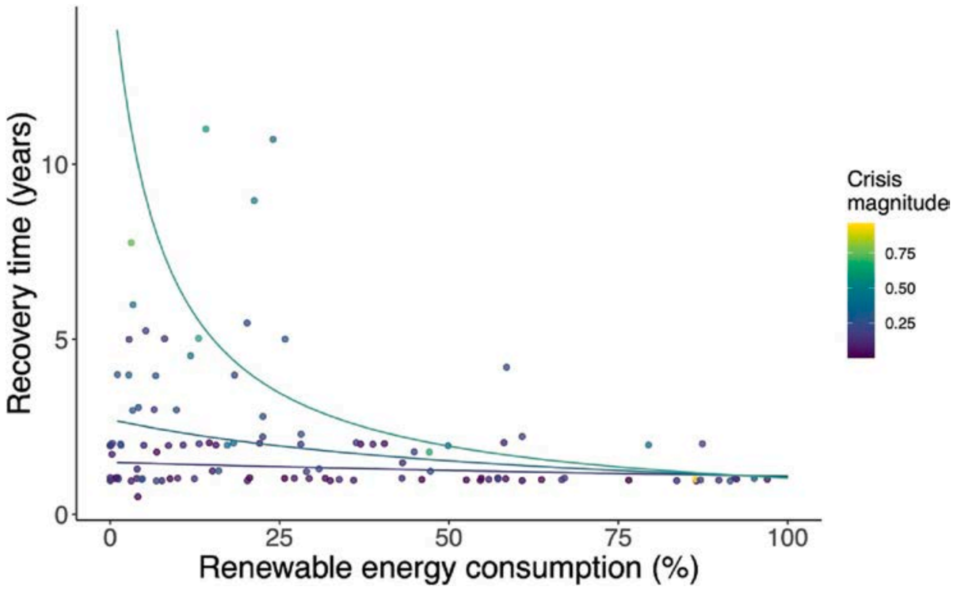

Fig. 4. Empirical relationship between renewable energy consumption and the recovery of real national economies after systemic crises. Scatterplot of the time taken for national economies to recover from systemic crises and the share of renewable energy in total energy consumption in the country. Points are for individual crisis events (n = 109), coloured by crisis magnitude (that is, the proportional reduction in GDP following the crisis). Lines correspond to GLMM model predictions for crises corresponding to drops of 20%, 40% and 60% of GDP. Model estimates and diagnostics are shown in, respectively, Table S3 and Fig. S1.

total energy consumption (Table S2). Specifically, we found that more rapid economic recovery from systemic crises was associated with greater extent of reliance by countries on renewable energy (Fig. 4). Moreover, this effect strengthened as the magnitude of crises increased (GLMM for interaction between renewable energy consumption and crisis magnitude: $t = 4.78$, $P < 0.00001$). Given that the data we analysed are taken from a widely diverse set of societies and economies, the model explains a remarkably high proportion of the variability in economic recovery time (pseudo-$r^2 = 0.86$), with renewable energy consumption explaining considerable variation over and above that accounted for by crisis magnitude alone (ΔAIC relative to the GLMM with crisis magnitude as the only fixed effect =111.2, pseudo-r^2 of the latter model = 0.61). In fact, the model including renewable energy consumption performed significantly better than both the number and evenness of electricity sources in explaining variance in economic recovery times (ΔAIC = 2.1 and 8.2, respectively; Table S3). Moreover, accounting for other factors also known to be associated with financial stability in the model (Schinasi, 2005; Shafiee and Topal, 2010; Haldane and May, 2011; Hamilton, 2011; Murphy and Hall, 2011; World Bank, 2014) did not alter our findings: greater national reliance on renewable energy was associated consistently with shorter economic recovery times from systemic crises even after the effects of GDP, the extent of domestic lending, fuel prices and national development status were accounted for (Table S4).

4. Discussion

Our findings provide novel insights into how the energy mix that powers national economies may also moderate their capacity to recover from systemic crises. Consistent with similar conclusions drawn from financial networks (Stiglitz, 2010; Haldane and May, 2011; Battiston et al., 2012; Bardoscia et al., 2017), our results suggest that diversification of the electricity production network via utilisation of greater numbers of electricity sources destabilizes economies by increasing their recovery time from shocks. However, our empirical findings also indicate that balancing contributions among electricity sources may help to mitigate to some extent the destabilizing influence of electricity diversification. Even though the number and evenness of electricity sources were related in opposite ways to economic recovery time in our empirical analysis, they nonetheless correlated positively with each other (Spearman $\rho = 0.29$, $P = 0.0006$). This would, in turn, imply that they influence economic stability through distinct mechanisms. Though our mathematical matrix model does not allow us to model evenness explicitly, as our random matrix model does not allow explicit modelling of the densities of natural resource sectors, it nonetheless provides potential insights into those mechanisms: whereas cascades of sector collapses are triggered when networks with high numbers of resource sectors are exposed to a shock, greater balance in the relative contributions of those sectors (that is, greater evenness in the system) would likely act to reduce the strength of intersectoral interactions, irrespective of whether they were competitive or cooperative, and hence buffer the system somewhat against the contagion spread of competitive or cooperative dominance.

The real-world crisis events analysed in our study vary significantly in terms of the local and global economic context in which they took place—their causes, the policy interventions undertaken to foster recovery and the national, regional and global extent of crises. The resulting myriad of interacting local and global factors would be expected to create significant variability in recovery dynamics across national economies. In spite of this considerable variation in our dataset, the vast majority (86%) of the variance in economic recovery time was, quite remarkably, accounted for by just crisis magnitude and the extent of reliance on renewable energy sources. Clearly, because our empirical results are based on correlative analyses from observational data, it is not possible to demonstrate causality and the relationships we observe may be driven indirectly by some, as yet unclear, source. Nonetheless, the extent of reliance on renewable energy sources remained a consistently important predictor of economic recovery time even when other key factors known to influence financial stability, such as GDP, the extent of domestic lending, fuel prices and national development status (Schinasi, 2005; Shafiee and Topal, 2010; Haldane and May, 2011; Hamilton, 2011; Murphy and Hall, 2011; World Bank, 2014), were accounted for.

Though our theoretical model provides some general insights into how the diversity of energy sources used in a country may influence its economic stability, the potential mechanisms through which reliance on renewable energy sources may act to enhance economic recovery remain unclear. Renewable energy is not always produced using sustainable renewable sources, as the use of “traditional biomass” as fuelwood frequently originates from unsustainable deforestation practices, particularly in developing countries (Goldemberg and Coelho, 2004). However, the fact that the extent of reliance on renewable energy sources remained a consistently important predictor of economic recovery time over and above the influence of development status suggests that the use of traditional biomass in this way does not affect our findings significantly. Key features of renewables that could promote economic stability include the fact that, because they in general comprise locally-produced indigenous sources of energy—a feature of both traditional and modern renewables—they do not display the high volatility of prices, lag times and accessibility displayed by other energy sources which are often imported, such as fossil fuels (Goldemberg and Coelho, 2004; Shafiee and Topal, 2009). They are also unlikely to contribute as strongly to GDP, thus potentially acting as a stable compartment within the financial ecosystem, a known source of stabilization in complex systems (May, 1972, 1973). Neither do they generate the same significant and increasing negative externalities as fossil fuels, which ultimately impair economic performance (Davidson and Andrews, 2013). The consequences of such negative externalities were exemplified clearly during the COVID-19 pandemic, as more stringent lockdown measures, and their associated severe economic impacts, were necessary in locations with higher exposure to air pollution and consequently higher mortality (Conticini et al., 2020; Wu et al., 2020). This has, in turn, brought about calls from expert groups and international organizations such as the World Bank and United Nations Environment Programme for economic recovery plans and investments to be based on renewable energy sources (Sinha, 2020; UNEP, 2020; World Bank, 2020).

GDP best describes the cumulative purely market value of national economic output over a year. It is (mis)used widely as a proxy for economic development and is the most important policy goal in almost every country (Costanza et al., 2014b; Ward et al., 2016). Given that it is also linked closely with energy use (Warr and Ayres, 2010; Ayres et al., 2013), and is conveniently estimated for all countries over time, GDP was the most appropriate basis with which to explore relationships between energy use and economic stability. GDP was, however, never designed as a measure of well-being, development, or social structure (Costanza et al., 2014b). Our results therefore provide little insight into the factors that govern recovery of these key features of socio-economic systems from shocks.

Though our empirical findings are purely correlative, and the mechanisms underpinning them therefore unclear, their potential implications for national and international energy policy are nonetheless profound and demanding of further exploration. In 2017, the global subsidy for fossil fuels was approximately $5.2 trillion, more than double the estimated subsidy to renewables (Coady et al., 2019). One of the most widespread responses to the 2008 global financial crisis was to increase investment in fossil fuels even further and divest from renewable energies. For example, in Italy between 2011 and 2012, investment in renewable energy was reduced by 51%. Worldwide, the corresponding decrease was 11% (UNEP, 2013). Our results suggest that such movement of national economies away from renewable energy sources could undermine economic stability and extend recovery times, particularly during times of crisis.

Our findings highlight the importance of the intrinsic link between natural resources provided by ecosystems and the stability of the economies that rely on them. Ultimately, they point to the need for a fundamental reassessment of both national and international energy policy, not only for the sake of our environment, but also to enhance the stability—and sustainability—of our economies.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All empirical data used in this manuscript are openly available online.

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Appendix A. Supplementary data

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