Journal of
Risk and Financial Management

Article

The Impact of Socioeconomic and Environmental Indicators on Economic Development: An Interdisciplinary Empirical Study

Antonio Pacifico

Department of Economics and Law, University of Macerata, Piazza Strambi 1, 62100 Macerata, Italy; antonio.pacifico@unimc.it

Abstract: This paper aims to investigate the effects of environmental sources and health statistics on economic growth and other development indicators of interest. With population growth, urbanization, and industrialization of economies, the built environment for human health has emerged as an important and growing driver in interdisciplinary research and evidence-based policy development, improving a country's growth prospects and the standard of living. A compressed structural Panel Vector Autoregression is used to address these issues. Methodologically, a hierarchical semiparametric Bayesian approach is involved to reduce the dimensionality, overtake variable selection problems, and model stochastic volatility. Policy-relevant strategies are also addressed to investigate causal relationships between sustainability indicators and economic growth.

Keywords: health economics; environment; Hierarchical Bayes approach; Monte Carlo algorithms; compressed regression; policy issues

check for updates

Citation: Pacifico, Antonio. 2023. The Impact of Socioeconomic and Environmental Indicators on Economic Development: An Interdisciplinary Empirical Study. *Journal of Risk and Financial Management* 16: 265. https://doi.org/10.3390/jrfm16050265

Academic Editors: Tiiu Paas and Hakan Eratalay

Received: 23 February 2023
Revised: 21 April 2023
Accepted: 26 April 2023
Published: 6 May 2023

1. Introduction

Interdisciplinary research refers to a significant transformation of knowledge through the integration of ideas and tools addressed by two or more research projects. In this study, methodological findings achieved in compressed regression models are combined for undertaking research on development and environment, and cross-country effects that this involves (see, e.g., Lawrence 2004; Handy et al. 2008; Briassoulis 1997; Max-Neef 1995; Reed et al. 2006; Turcu 2013; McNeill 1999, and Oreskes et al. 1994). The empirical application evaluated by means of more than hundreds of macroeconomic–financial and socioeconomic variables in a pool of advanced and developing countries describes the estimating procedure. It approaches three main macroeconomic issues: (i) the existence of (potential) causal relationships between health and environment indicators among developed and developing countries; (ii) the presence of unobserved cross-country interlinkages and dynamic feedback over time; and (iii) the role of economic–financial factors and policy issues when studying multicountry economic dynamics in panel setups.

Let the evidence on the role of the built environment in promoting human health, infrastructure, and manufacturing services be known, while the study of causal relationships between healthy built environments and other economic–financial variables of interest is also compelling. Indeed, in recent decades, much progress has been achieved in connecting the people of the world to reliable improvements in health, highlighting an existing causal effect on economic growth, poverty, and other development indicators of interest (see, e.g., McLeroy et al. 1988; Stokols 1996; Sallis et al. 2006; Pilkington et al. 2008 and Vecchiarelli et al. 2005). However, empirical evidence of the causal effect of health and the built environment on economic growth is weak and most existing studies found contrasting and inconclusive results because of inappropriate methodological approaches, shorter time series to investigate potential causal effects, and high attention toward developed countries (see, among many others, Granger 1969; Lütkepohl 1982; D'Acci 2011; and Diener and Suh 1997). Even if it would be simpler to find evidence for causal effects using disaggregated micro-level data because some variables can more easily be considered exogenous and other field experiments are possible, growth is an economy-wide, dynamic, and long-term process with effects that are unlikely to be captured in micro setups (see, among many others, Borenstein 2015; Dobbie and Dail 2012; Freebairn and King 2003; and Niemeijer and Groot 2008). Thus, cross-country macroeconomic–financial linkages and interactions need to be dealt with (see, for instance, Barro 2003; Canova and Ciccarelli 2009, 2016; Canova and Forero 2015; Pacifico 2019, 2020a, 2021).

Most empirical analysis has been conducted on the economic implications of healthy built environments in developed countries by considering health as an important driver of economic growth when they have been at lower income levels (see, for instance, Gahin et al. 2003; Jesinghaus 2012 and Singh et al. 2009). Over time, growing evidence has shown that the two seemingly disparate professions can work together, continuing to improve their collaborative endeavors and support the ongoing development of the interdisciplinary practice of healthy planning (see, for instance, McLeroy et al. 1992; Macintyre et al. 2002; Thompson 2000; Wooten 2010 and Krajnc and Glavič 2005). Nevertheless, some shortcomings of these studies are that they ignore possible endogeneity and spatial interdependence between the built environment and health problems (such as hypertension, depression, obesity), negatively affecting economic development and labor market performance (see, e.g., Feng et al. 2010; Brownson et al. 2006; Dodson et al. 2009; Black and Macinko 2008 and Coveney and O'Dwyer 2009). Recent studies highlighted the strict relationship between physical appearance and economic growth, affecting—in turn—the individual's capacity to work (see, e.g., Böckerman et al. 2019; Cawley 2015; Puhl and Brownell 2001 and Angrisani et al. 2018). Indeed, obese workers could be related to non-desirable personality traits potentially, resulting in worse labor market outcomes (see, e.g., Hamermesh and Biddle 1994; Baum and Ford 2004; Rooth 2009 and Sobal 2004).

The computational approach proposed in this paper focuses on the aforementioned issues and aims to deepen the topic of the causal relationship between socioeconomic indicators, economic development, and macroeconomic variables of interest. It is evaluated building on Pacifico (2022b)'s analysis, which estimated a Structural Bayesian Compressed Panel Vector Autoregressive (SBCPVAR) model with time-varying parameters and multivariate stochastic volatilities. Conversely to the standard Bayesian compressed regression and VAR models, it involves a shrinking open robust Bayesian Model Averaging (BMA) procedure. Here, `open` refers to the use of Markov Chain Monte Carlo (MCMC) algorithms rather than recursive discriminant analysis, and `robust` stands for the construction of multivariate conjugate informative priors rather than single priors. In this way, a large panel of data accounting for different areas of research can be included in the system and jointly evaluated minimizing some high-dimensional problems such as endogeneity and model misspecification.

The contributions of this paper are threefold. First, semiparametric prior specification strategy is developed using multivariate Conjugate Informative Proper Mixture (mvCIPM) priors to select the `best`[1] model solution (or combination of predictors) fitting the data (see, for instance, Pacifico 2020b). Second, MCMC algorithms based on Posterior Model Probabilities[2] (PMPs) are used to construct posterior distributions and shrink jointly parameter and model space to perform business strategies and policy issues. Third, a generalized version of the Granger (Non-)Causality test is conducted in the reduced subset of predictors to verify whether strong causal relationships matter for a subgroup of units (see, e.g., Dumitrescu and Hurlin 2012 concerning dynamic panel data).

An interdisciplinary empirical study is conducted involving large panel sets of macroeconomic, environmental, and socioeconomic variables in a pool of advanced and developing countries. The main thrust is to combine some open research issues in accordance with the impact of environment source, health statistics, and other development indicators of interest in economic growth. Potential causal relationships and policy issues between the most suitable subset of predictors can also be investigated. The empirical strategy covers the period 1995–2020, where natural conjugate priors are involved in dealing with potential (unobserved) structural breaks: 2007, due to the global financial crisis; 2011–2014, due to fiscal recovery programs; and 2019 due to the COVID-19 pandemic. Forecasting is then conducted over a time frame of nine quarters (two years and a quarter) to absorb spillover effects affecting cross-country economic dynamics due to the economic and social disruption caused by the pandemic and Russia-Ukraine war.

The outline of this paper is as follows. Section 2 discusses the econometric methodology and the Bayesian strategy, clarifying prior assumptions and posterior distributions involved in the dynamic analysis. Section 3 illustrates the cross-country empirical analysis, emphasizing the role of the built environment in promoting human health sources, and how possible causal links between socioeconomic indicators and economic development matter. Section 4 contains some concluding remarks.

2. Econometric Methodology

2.1. Estimation Procedure

The multicountry SPBVAR model used in this study has the form:

$$Y_{im,t} = \sum_{\lambda=1}^{l} \left[A_{im,j\tilde{m}}(L) Y_{im,t-\lambda} + B_{i\xi,j\tilde{\xi}}(L) Z_{i\xi,t-\lambda} \right] + \varepsilon_{im,t} \quad , \tag{1}$$

where the subscripts $(i,j) = 1,2,\ldots,N$ and $t = 1,2,\ldots,T$ are country indices and time periods, respectively, $m = 1,2,\ldots,M$ and $\xi = 1,2,\ldots,\Xi$ refer to the variables included in the system for i, with $\tilde{m} = 1,2,\ldots,\tilde{M}$ and $\tilde{\xi} = 1,2,\ldots,\tilde{\Xi}$ denoting the indices observed for j independent of i, $\lambda = 1,2,\ldots,l$ denotes lagged periods, $Y_{im,t}$ is a $NM \cdot 1$ vector of observed outcomes to be predicted for each i, $Y_{im,t-\lambda}$ and $Z_{i\xi,t-\lambda}$ are $NM \cdot 1$ and $N\Xi \cdot 1$ vectors of observed lagged variables and additional lagged factors for each i for a given m and ξ, respectively, $A_{im,j\tilde{m}}$ and $B_{i\xi,j\tilde{\xi}}$ are $NM \cdot NM$ and $N\Xi \cdot N\Xi$ matrixes of time-varying coefficients for each pair of countries (i,j) for a given m and ξ, respectively, and $\varepsilon_{im,t} \sim i.i.d.N(0,\Omega_t)$ is a $NM \cdot 1$ vector of heteroschedastic unobservable shocks with variance-covariance matrix Ω_t.

To investigate the effects of health and environment indicators on economic growth and potential relationships with other development factors, we decompose the variables in a conditioning set $c_{it,j}$: $Y_{im,t-\lambda} = \left[Y^{o'}_{im,t-\lambda}, Y^{c'}_{im,t-\lambda} \right]'$, with $Y^{o'}_{im,t-\lambda}$ denoting lagged outcomes such as economic growth and $Y^{c'}_{im,t-\lambda}$ including lagged control variables such as economic development indicators; and $Z_{i\xi,t-\lambda} = \left[Z^{s'}_{i\xi,t-\lambda}, Z^{h'}_{i\xi,t-\lambda} \right]'$, referring to additional factors such as socioeconomic conditions ($Z^{s'}_{i\xi,t-\lambda}$) and health issues ($Z^{h'}_{i\xi,t-\lambda}$). Then, let $k = [M + \Xi] \cdot l$ correspond to the number of all matrix coefficients in each equation of model (1), with $k = 1,2,\ldots,\bar{k}$, I group all covariates into a $1 \cdot Nk$ vector $X_t = (Y'_{im,t-1}, Y'_{im,t-2}, \ldots, Y'_{im,t-l}, Z'_{i\xi,t-1}, Z'_{i\xi,t-2}, \ldots, Z'_{i\xi,t-l})'$ and all time-varying parameters into a $NM \cdot Nk$ matrix $\Theta_t = (A_{im,j1}, A_{im,j2}, \ldots, A_{im,j\tilde{M}}, B_{i\xi,j1}, B_{i\xi,j2}, \ldots, B_{i\xi,j\tilde{\Xi}})$.

Four important features matter. First, the use of a hierarchical framework and variable selection procedure to make the model (1) feasible and reliable because of (possible) different dimensions between matrixes $(A_{i,j}, B_{i,j})$. Second, the use of random walk processes ensures that multiple change points are evaluated when modeling time-varying coefficients and shrinking a large set of indicators in a lower-dimensional space. Third, even if the block diagonality of Σ_δ guarantees the identifiability of the δ_t's, Bayesian inference is involved to also identify `excessive` volatility changes and replace them by coefficient changes, where `excessive` stands for a sudden high time-varying volatility. The latter is evaluated using the excess kurtosis index according to the information over the past. Fourth, the heteroscedasticity imposed in the variance-covariance matrix of $\varepsilon_{i,t}$ is able to capture potential unobserved shocks (impulse) among variables and countries affecting outcomes (response). Indeed, when studying macroeconomic–financial linkages and other related socioeconomic–development indicators, the model (1) would involve multiple and multivariate structural breaks. Thus, the error terms in (1) are rewritten as

$$\varepsilon_{i,t} = \Delta_t \cdot \omega_{i,t} \quad \text{with} \quad \Omega_t = \Delta_t \Delta_t^{'} \quad , \tag{2}$$

where Δ_t is an $NM \cdot Nk$ matrix with elements equal to (absence of volatility changes) or different from (presence of volatility changes) zero, and $\omega_{i,t} \sim N(0, I_{Nk})$ is a $Nk \cdot 1$ vector for each set of variables (m, ξ). Let $\delta_{i,t} = vec(\Delta_t) = vec(d^{'}_{im,j1}, d^{'}_{im,j2}, \ldots, d^{'}_{im,j\bar{k}})^{'}$ be a $NMK \cdot 1$ vector, with $K = Nk$, containing the elements of the matrix $\Delta_{i,t}$ stacked by columns, the parameter $\delta_{i,t}$ is modeled as a random walk process:

$$\delta_t = \delta_{t-1} + v_t \quad \texttt{where} \quad v_t \sim N(0, \Sigma_\delta) \quad , \tag{3}$$

where $\Sigma_\delta = diag(\sigma^2_{d_{im,j1}}, \sigma^2_{d_{im,j2}}, \ldots, \sigma^2_{d_{im,j\bar{k}}})$ is a block diagonal covariance matrix of size $NM \cdot K$, and δ_0 denotes the initial conditions to be estimated.

With these specifications, model (1) can be expressed in a simultaneous-equation form:

$$Y_t = \Theta_t X_t^{'} + \Delta_t \omega_{i,t} \quad , \tag{4}$$

where $Y_t = (Y^{'}_{1m,t}, \ldots, Y^{'}_{Nm,t})^{'}$ and $X_t^{'}$ is a $NM \cdot 1$ vector containing the observable variables of interest. Let $\gamma_t = vec(\Gamma_t)$ be a $NMK \cdot 1$ vector containing the time-varying parameters and volatilities stacked into a vector, where $\Gamma_t = (\Theta_t, \Delta_t) = (A_{im,j1}, \Delta_t\ ,\ A_{im,j2}, \Delta_t\ ,\ \ldots,\ A_{im,j\tilde{M}}, \Delta_t\ ,\ B_{i\xi,j1}, \Delta_t\ ,\ B_{i\xi,j2}, \Delta_t\ ,\ \ldots\ ,\ B_{i\xi,j\bar{\Xi}}, \Delta_t)$ is an auxiliary $NM \cdot Nk$ matrix built to combine the coefficient vectors of $(A_{i,t}, B_{i,j})$ with the elements of Δ_t. The reduced form in (4) can be rewritten in a compressed regression form:

$$Y_t = \Gamma_t \left(X_t^{'} + \omega_{i,t} \right) \quad . \tag{5}$$

The variable selection procedure entails when some unknown subset of X_t—grouped in γ_t—is so small that it would be preferable to discard it ($\gamma_t = 0$). In this framework, two auxiliary indicator variables are used: $N\varphi \cdot 1$ vector ϕ_t containing the compressed γ_t's parameters (γ_t^c) and a $NMK \cdot 1$ vector β_t containing all 2^K possible model solutions, with $\varphi \ll K$ denoting the compressed regression coefficients. Furthermore, the γ_t^c's parameters are assumed to follow the below factor structure:

$$\gamma_t^c = \Phi_t \cdot \phi_t + u_t \quad , \tag{6}$$

where $dim(\phi_t) \ll dim(\gamma_t)$ by construction, $N\phi \ll NMK$ denotes the length of the lower-dimensional parameter space obtained through the shrinking process, Φ_t is a $NMK \cdot N\varphi$ conformable matrix with elements equal to zero (absence of K-th covariate in the model) and one (presence of K-th covariate in the model), and u_t is a $NMK \cdot 1$ vector of disturbances. Both the auxiliary variable ϕ_t and the error term u_t are supposed to be distributed as further random walk processes:

$$\phi_t = \phi_{t-1} + \eta_t \quad \text{with} \quad \eta_t \sim N(0, \Upsilon_t) \quad ; \tag{7}$$

$$u_t = u_{t-1} + \varsigma_t \quad \text{with} \quad \varsigma_t \sim N(0, \Sigma_u) \quad . \tag{8}$$

Here, $\Sigma_u = V \cdot \sigma_t$, with $V = \sigma^2 \cdot I_{NMK}$ as in Kadiyala and Karlsson (1997) and $\sigma_t \cong \Omega_t \otimes (X_t^{'} X_t)$ denoting (potential) volatility changes, $\Upsilon_t = diag(\Upsilon_{mt,1}, \Upsilon_{mt,2}, \ldots, \Upsilon_{mt,\bar{k}})$ is a block diagonal matrix, with $\Upsilon_{mt,k} = (v_{mt,k} \cdot I_{NMK})$ and $v_{mt,k}$ controlling the stringent conditions of the shrinking process to make the time-varying γ_t^c's regression coefficients estimable. The error terms u_t and v_t are correlated between them by construction, but η_t and v_t can be uncorrelated.

Finally, according to the factorization in (6) and let $\tilde{X}_t = I_{NM} \otimes (X_t + \omega'_{i,t})$ be an $NM \cdot NMK$ matrix containing all (lagged) time-varying variables and volatilities stacked in X_t and $\omega_{i,t}$, respectively, the compressed regression model in (5) can be better displayed in the form of a Compressed Seemingly Unrelated Regression (CSUR) model:

$$Y_t = \tilde{X}_t \Big[\Big(\Phi_t \cdot \phi_t \Big) + u_t \Big] \equiv \chi_t^c \phi_t + E_t^c \quad , \tag{9}$$

where $\chi_t^c \equiv (\tilde{X}_t \cdot \Phi_t)$ are $NM \cdot N\varphi$ matrixes stacking all coefficients and their possible interactions evaluated in (1), and $E_t^c \equiv \tilde{X}_t \cdot u_t$ is an $NM \cdot 1$ vector disturbance terms.

2.2. Shrinking Procedure

The main thrust of the variable selection procedure is to discard the γ_t's predictors from the procedure when sufficiently small, and then obtain a lower-dimensional parameter space of size $N\phi \ll NMK$.

Let $M_K = (M_{i1}, M_{i2}, \ldots, M_{i\bar{k}})$ be a countable collection of all (potential) 2^K model solutions—evaluated through the auxiliary parameter γ_t—the full model class set is:

$$\mathcal{F} = \Big\{ M_K : M_K \subset \mathcal{F}, M_K \in \mathcal{M}, k \in \mathcal{K}, \ \Theta_t X'_t + \Delta_t \omega_t \Big\} \quad , \tag{10}$$

where $\mathcal{M}$ and $\mathcal{K}$ denote the multidimensional natural model and parameter space, respectively. Thus, the related probability of each candidate model in fitting the data (PMPs) are defined as:

$$\pi(M_K|Y_t) = \frac{\pi(Y_t|M_K) \cdot \pi(M_K)}{\sum_{M_K \in \mathcal{M}} \pi(Y_t|M_K) \cdot \pi(M_K)} \quad , \tag{11}$$

where $\pi(Y_t|M_K) = \int \pi(Y_t|M_K, \phi_t) \cdot \pi(\phi_t|M_K) d\phi_t$ is the marginal likelihood, and $\pi(\phi_t|M_K)$ is the conditional prior distribution of ϕ_t given M_K. However, when N is high-dimensional and T sufficiently large, the calculation of the integral $\pi(Y_t|M_K)$ is unfeasible, and then a prior specification strategy and MCMC algorithms have to be involved.

Conversely to Pacifico (2022b), in this study, the final model solution is obtained in a unique step, and causal relationships are then tested on the compressed subset of predictors. Thus, the full set in (6) will be reduced in a lower-dimensional model class:

$$\mathcal{E} = \Big\{ M_F : M_F \subset \mathcal{E}, \mathcal{E} \subset \mathcal{F}, \sum_{M_K \in \mathcal{M}} \pi(M_F|Y_t, \phi_t) \geq \tau \Big\} \quad , \tag{12}$$

where M_F denotes the subset containing the `best` model solutions of the CSUR in (9), with $M_F < M_K$, $F \ll K$, $\{1 \leq \varphi < k\}$, and τ referring to an arbitrary threshold for achieving enough posterior consistency. In this study, $\tau = 1\%$, resulting in being (slightly) more restrictive than that used in Pacifico (2022b). More precisely, the choice is because of high-dimensional N, much larger than the observational units used in Pacifico (2022b)'s case study (43 vs. 24), and more time periods T (129 vs. 117). Moreover, the aim of this study consists of addressing an interdisciplinary empirical study when combining more than one assignment (such as environment source, health issues, and development indicators). Thus, problems related to the overestimation of effect sizes (or individual combinations) and dynamic interactions (or cross-term lagged interdependencies) have to also be dealt with.

The shrinking procedure is completed by choosing the `best` final model solution. It corresponds to one of the submodels M_F with higher log natural Bayes Factor (lBF):

$$lBF_{\varphi,k} = log \left\{ \frac{\pi(M_F|Y_t)}{\pi(M_K|Y_t)} \right\} \quad . \tag{13}$$

In this analysis, the lBF is interpreted according to the scale evidence in Pacifico (2022b) but with fewer restrictions to deal with some data-mining concerns such as different kinds of knowledge in databases, presence of noisy or incomplete data, and pattern evaluation:

$$\begin{cases} 0 \leq lBF_{\varphi,k} < 1.99 & \text{no evidence for submodel } M_F \\ 3 \leq lBF_{\varphi,k} < 4.99 & \text{moderate evidence for submodel } M_F \\ 6 \leq lBF_{\varphi,k} < 7.99 & \text{strong evidence for submodel } M_F \\ lBF_{\varphi,k} \geq 8.00 & \text{very strong evidence for submodel } M_F \end{cases} \tag{14}$$

2.3. Dynamic Investigation

The variable selection procedure entails estimating the parameters $(\Sigma_\delta, \delta_t, \phi_t, \beta_t, v_t)$ as posterior means[3]. Then, mvCIPM priors are used to hierarchically model them:

$$\pi\left(\Sigma_\delta^{-1}, \delta_0, \phi, v_0\right) = \pi\left(\Sigma_\delta^{-1}\right) \cdot \prod_F \pi(\delta_0) \cdot \pi(\phi) \cdot \prod_F \pi(v_0) \quad , \tag{15}$$

where

$$\pi\left(\Sigma_\delta | Y_t\right) = IIG\left(\frac{\bar{\omega}}{2}, \frac{\bar{D}}{2}\right) \quad , \tag{16}$$

$$\pi(\delta_0 | \mathcal{F}_{t-1}) = N(0, \varkappa) \quad , \tag{17}$$

$$\pi(\phi_t | \Sigma_\delta, Y_t) = N\left(\bar{\phi}_{t-1|t-1}, \bar{R}_{t-1|t-1}\right) \quad , \tag{18}$$

$$\pi(v_0 | \mathcal{F}_{t-1}) = IG\left(\frac{\vartheta_0}{2}, \frac{S_0}{2}\right) \quad . \tag{19}$$

Here, $N(\cdot)$ and $IG(\cdot)$ stand for Normal- and Inverse-Gamma distribution, respectively, $\mathfrak{F}_{t-1}$ refers to the information given up to time $t-1$, Σ_δ in (16) is modeled through an Independent Inverse Gamma (IIG) distribution to disentangle the dependency between ϕ_t and Σ_δ, with $\bar{\omega}_0$ and $\bar{D}_0$ denoting the initial conditions to be estimated, and $\varkappa$ in (17) denotes the decay factor. This latter usually varies in the range [0.9–1.0] and controls the process of reducing past data by a constant rate over a time period. Finally, let the data run $(t = 0)$ to $(t = T)$ with training sample $\{t-1, 0\}$, and the hyperparameters in identifying ϕ in (18) are further modeled via a variant of the Gibbs sampler approach (Kalman-filter technique):

$$\pi(\phi_t | \phi_{t-1}, Y_t) = N\left(\bar{\phi}_{t|t}, \bar{R}_{t|t}\right) \quad , \tag{20}$$

where $\bar{\phi}_{t|t}$ and $\bar{R}_{t|t}$ denote the conditional distribution of ϕ_t and its variance-covariance matrix at time t given the information over the sample $\{t-1, 0\}$, respectively. All the hyperparameters involved in the mvCIPM priors are known and collected into a vector $\varrho = (\omega_0, D_0, \vartheta_0, S_0)$[4].

The conditional posterior distribution of $(\phi_1, \ldots, \phi_T | Y_T)$ is obtained from forward recursions for posterior means $(\bar{\phi}_{t|t+1})$ and covariance matrix $(\bar{R}_{t|t+1})$:

$$\pi(\phi_t | \phi_{t-1}, Y_T) = N\left(\bar{\phi}_{t|t+1}, \bar{R}_{t|t+1}\right) \quad . \tag{21}$$

According to Pacifico (2022b), the other posterior distributions are defined as:

$$\pi\left(\Sigma_\delta | Y_T\right) = IIG\left(\frac{\hat{\omega}}{2}, \frac{\hat{D}}{2}\right) \quad , \tag{22}$$

$$\pi(\delta | Y_T) = N(0, \hat{\varkappa}) \quad , \tag{23}$$

$$\pi(v|Y_T) = IIG\left(\frac{\bar{\vartheta}}{2}, \frac{\bar{S}}{2}\right) \quad . \tag{24}$$

Evaluating an interdisciplinary empirical study over a large set of different indicators, some restrictions on the estimated hyperparameters are accounted for. In Equation (22), $\hat{\omega} = \bar{\omega}_0 \cdot \bar{\omega}$ and $\hat{D} = \bar{D}_0 \cdot \bar{D}$, with $\bar{\omega}_0 \cong 0.001$, $\bar{D}_0 \cong 0.90$, and $\varkappa = 0.90$. In this study, initial conditions of $\bar{D}_0$ and the decay factor coincide to ensure identification. In Equation (23), $\hat{\varkappa} = \varkappa \cdot exp\{0.3 \cdot \kappa\}$. The time of constant volatility ($\kappa = 0$), $\hat{\varkappa}$ will be close to the decay factor (0.90); conversely, in case of very large volatility changes (e.g., $\kappa \cong 1.0$), $\hat{\varkappa}$ will assume higher values. In Equation (24), $\bar{\vartheta} = \vartheta_0 \cdot \varpi$ and $\bar{S} = S_0 + \hat{\varkappa}$, with $\vartheta_0 = 0.001$ and $S_0 = 0.1$.

3. Empirical Application

3.1. Data Description and Results

The model is estimated for 43 country-specific models, referring to 22 developed economies and 21 developing countries. The estimation sample covers the period from March 1990 (1990:q1) to December 2020 (2020:q4). Only one lag has been chosen to ensure stationarity among all series. The dataset contains 153 observable variables split into three groups: `(i)` MACROECONOMIC–FINANCIAL INDICATORS, including 61 variables combining information on economic development, financial markets, and labor force; `(ii)` SOCIOECONOMIC–HEALTH STATUS, addressing 47 factors concerning information on health determinants and population growth; and `(iii)` ENVIRONMENTAL SOURCE, referring to 45 covariates dealing with environment, high-technology, and energy use.

By running the shrinkage procedure, 26 predictors better fit the data and then there are $2^{Nf} = 2^{1118}$ compressed model solutions ($M_F \subset \mathcal{E}$). The final `best` model solution performing the data consists of 12 covariates with Posterior Inclusion Probability (PIP) $\geq \tau$ and higher log Bayes Factor equals to 11.53 (Table 1 in bold). The PIP corresponds to the sum of the PMPs in (11) computed for every model solution for all M_K models wherein a covariate X_t has been included with the auxiliary variable γ_t.

All of their lags are put as `external` instruments in the estimation model to capture some exogenous variations because of endogeneity issues, functional forms of misspecification, and dynamic causal effects. `External` instruments refer to variables correlated with a shock of interest, but not with other shocks.

In Table 1, the Conditional Posterior Sign (CPS) denotes the sign certainty assuming values close to 1 or 0 whether a covariate has a positive or negative effect on the outcomes of interest, respectively. It is better emphasized displaying the CSUR estimates (Table 2).

Let the final subset consist of 12 final `best` covariates; a total of 10,000 draws for every model solution has been used to conduct posterior inference at each t. Conditional density forecasts are then obtained according to a time frame of nine quarters (two years and a quarter) in order to assess interdisciplinary research on how a set of different indicators and their interactions affect cross-country economic dynamics.

Some preliminary empirical results are addressed. `(i)` Socioeconomic–health indicators and general economic conditions hold a relevant position when studying dynamic feedback such as cross-country spillover effects. `(ii)` Macroeconomic–financial linkages have to be accounted for, representing the most relevant indicators to evaluate economic dynamics. `(iii)` Heterogeneity, interdependence, and co-movements are also addressed; let the framework be hierarchical. `(iv)` A multidimensional panel setup is useful to also address causal relationships when dealing with a large set of different variables. `(v)` Multicollinearity problems are dealt with using lagged variables as `external` instruments.

The CSUR estimates are displayed in Table 2. From a modeling perspective, economic and financial indicators strongly positively affect productivity levels, except for the inflation rate. Indeed, according to the CPS in Table 1, the predictor 9 has to be evaluated with care, displaying mixed effects. More precisely, the results of the empirical evidence on the inflation-productivity relationship are mixed because of sensitivity to the inclusion of additional variables as determinants of productivity growth. Indeed, many studies suggest a link between inflation and economic conditions across countries (long-run effect), highlighting that high rates of inflation would create distortions leading to inefficient resource allocation and then lower productivity levels (see, among many others, Levine and Renelt 1992; Stock and Watson 1988; Watson 1994 and Blanchard and Quah 1989). Conversely, related works argue the existence of a causal interpretation and policy implication (cyclical comovements), emphasizing that lower inflation would increase productivity (see, among many others, Fischer 1993; Feldstein 1982; Canova et al. 2012 and King and Watson 1992). Health status, social factors, and environmental indicators significantly affect outcomes and—for the most part—negatively so. Positive effects are highlighted according to predictors 14, improving (general) health statistics, and 25, increasing the economic conditions. Predictor 10, such as predictor 9, has a negative impact on productivity levels displaying a not sufficiently high CPS. Finally, even if the use of the Internet would positively affect the outcomes of interest, it should be analyzed with care because of a CPS large but not quite close to 1. Indeed, productivity growth effects from the Internet have been positive and strictly significant over time, but with a significant decrease in the last decade (see, for instance, Gordon 2002; Maurseth 2018; Choi and Yi 2009 and Sichel 1999).

Table 1. Final `Best` Predictors.

Idx.	Predictor	Label	PIP (%)	CPS
	Macroeconomic–financial Indicators			
1	Weighted income per capita	`weig`	**62.12**	0.95
2	Expenditure on R&D	`rdexp`	0.34	0.64
3	Final consumption expenditure	`fexp`	**53.83**	0.96
4	GDP per capita growth	`gdpg`	**79.23**	1.00
5	GDP per capita, PPP	`gdp`	0.29	1.00
6	Labour force	`labtot`	**47.58**	0.95
7	Poorly paid job	`ppjob`	0.41	0.28
8	Gross fixed capital formation	`gfcf`	**67.52**	0.98
9	Consumer price index	`infl`	**38.76**	0.33
	Socioeconomic and Health Status			
10	Overweight	`obe`	**45.93**	0.27
11	Cultural interests	`cult`	0.25	0.44
12	Social participation	`socio`	0.27	0.68
13	Risk of poverty	`pover`	0.18	0.19
14	Current health expenditure	`hexp`	**75.13**	0.96
15	Total population age (15-above)	`pop`	0.38	0.52
16	Population Growth	`popg`	**55.21**	0.98
17	Rural population	`rpop`	0.15	0.62
18	Urban population	`upop`	0.17	0.65
19	Employment to population ratio	`epop`	0.31	0.99
	Environmental Source			
20	Exports of goods and services	`exp`	0.37	0.86
21	Imports of goods and services	`imp`	0.44	0.91
22	Energy use	`use`	**68.35**	0.95
23	Energy net imports	`import`	0.36	0.53
24	Individuals using Internet	`int`	**58.74**	0.82
25	High-technology exports	`hexports`	**65.72**	0.98
26	Trade	`trade`	0.24	0.92
-	productivity	`prod`	-	-

The table is so split: the first column denotes the predictor number; the second and the third column display the predictors and their labels, respectively; and the last two columns display the PIPs (in %) and the CPS, respectively. The last row refers to the outcomes of interest at time t corresponding to the productivity level in a given country, which refers to the real GDP per capita in logarithmic form. All data refer to OECD and Eurostat databases.

Finally, potential (unobserved) structural breaks and spillover effects affecting estimates and forecast results are absorbed within the system because of the use of conjugate informative priors. They correspond to strictly exogenous factors added in the final subset as permanent shifts, and evaluated through the Chow test. More precisely, two `dummies` were involved within the system: X^*_{1t}, time-fixed effects due to triggering events (such as global financial crisis, pandemic disease, inflation in the aftermath of wars and pandemics)[5]; and X^*_{2t} time-fixed effects due to fiscal policy implications (such as European recovery programs). The effects are significant and negatively and positively affected by productivity, respectively, as in Table 2.

Table 2. Compressed SUR Results.

Idx.	Variables	CSUR Model
	Macroeconomic–financial Indicators	
1	`weig`	3.84 *** (0.23)
3	`fexp`	9.32 *** (2.52)
4	`gdpg`	8.58 *** (3.23)
6	`labtot`	5.33 ** (3.16)
8	`gfcf`	1.91 *** (0.30)
9	`infl`	−1.71 *** (0.65)
	Socioeconomic and Health Status	
10	`obe`	−1.91 ** (0.80)
14	`hexp`	8.76 *** (2.26)
16	`popg`	−1.95 *** (0.32)
	Environmental Source	
22	`use`	1.89 *** (0.47)
24	`int`	−2.43 *** (0.34)
25	`hexports`	2.68 *** (0.44)
	Exogenous Factors	
-	X^*_{1t}	−3.27 *** (0.17)
-	X^*_{2t}	2.76 *** (0.21)

The first two columns denote the predictor number and labels, and the last column displays the estimates and the standard errors (in parenthesis). The significant codes are: *** significance at 1%; ** significance at 5%.

Table 3 displays the main diagnostic tests accounting for significance, robustness, and stationarity. Here, some considerations are in order. `(i)` The structural compressed regression in (9) is robust by explaining most of the variability of the outcomes of interest ($R^2_{adj.} \geq 87\%$). `(ii)` The Sargan–Hansen test of overidentifying restrictions (Q_S) highlights the usefulness of a multidimensional (panel) framework to deal with endogeneity issues and model misspecification problems (see, for instance, Bowsher 2002). In addition, the findings also highlight that—through the estimated CSUR model—one is able to address variable selection problems such as model uncertainty and overfitting. Indeed, the CPS of the final `best` predictors in Table 1 are close to 1 or 0. `(iii)` The estimates are robust and efficient showing linear dependencies among series and no serial correlations among residuals over time according to Arellano (2003) (Q_A) and Ljung-Box test (Q_{LB}), respectively. `(iv)` Let the framework be multidimensional, and panel unit root tests are also assessed through the Hadri (2000)'s test statistic (U_H), rejecting the null of nonstationary for all series. (v) The validity of the model also confirms the accuracy of the arbitrary threshold (τ) chosen in the computational approach.

Table 3. Diagnostic Tests.

Test Statistic	CSUR Model
Significance, Robustness, & Stationarity	
$R^2_{adj.}$	0.87
Q_S	138.24 (0.00)
Q_A	1.67 (0.13)
Q_{LB}	0.07 (0.71)
U_H	−2.61 (0.06)

The table refers to the test statistics and the corresponding p-values (in parenthesis) dealing with the significance, robustness, and stationarity of the structural compressed regression. They are $R^2_{adj.}$, Sargan's test for over-identification (Q_S), Arellano's serial correlation test (Q_A), and Multivariate Ljung-Box Tests for serial correlations among residuals over time (Q_{LB}). The panel unit root test refers to the Hadri (2000)'s (U_H) analysis.

The presence of Granger causality when studying heterogeneous dynamics is displayed in Table 4. It is tested through a generalized version of the Granger (Non-)Causality of Dumitrescu and Hurlin (2012) referring to dynamic data in a context of multivariate time series. The test statistic is the $\tilde{Z}$ used in Dumitrescu and Hurlin (2012), where the degrees of freedom at the denominator denote the final subset $\mathcal{E}$. Under the null hypothesis, there is no causal relationship among outcomes and predictors for any observation unit (country), whereas there are causal links for at least a subgroup of countries under the alternative. As is already known, when dealing with time-varying variables, estimates accounting for lagged variables would be biased if tested under the wrong hypothesis (see, for instance, Pesaran and Smith 1995). Moreover, if coefficient homogeneity is imposed, causality test statistics may lead to fallacious inference (or risk of failing to reject the wrong hypothesis). The resulting estimates displayed in Table 4 show that the null of non-causality is rejected for all variables and then dynamic feedback and cross-unit interdependencies matter. These findings would emphasize the computational approach addressed in this study.

Table 4. Granger Causality Test.

Idx.	Variables	$\tilde{Z}$ Test Statistic
	Macroeconomic–financial Indicators	
1	`weig`	13.19 ***
3	`fexp`	3.08 **
4	`gdpg`	28.61 ***
6	`labtot`	4.43 **
8	`gfcf`	21.12 ***
9	`infl`	−7.92 ***
	Socioeconomic and Health Status	
10	`obe`	−8.56 **
14	`hexp`	25.90 ***
16	`popg`	3.45 **
	Environmental Source	
22	`use`	22.55 ***
24	`int`	5.71 ***
25	`hexports`	15.23 ***

The first two columns denote the predictor number and labels, and the last column displays the $\tilde{Z}$ test statistics. The significant codes are: *** significance at 1%; ** significance at 5%.

3.2. Recommendations and Policy Improvements

The interdisciplinary empirical study has been addressed by first reviewing the literature for practical guidance from the above case study example and then discussing which socioeconomic and financial indicators strongly affect economic growth. According to the estimation results, the findings highlight a defined role for health status and related determinants and that economic conditions in a given country are important drivers (Table 1). However, when is the evidence of relationships between socioeconomic–financial and economic development 'good enough' to involve policy regime shifts? This study finds that the relationships between countries' productivity and environment source are driven by macroeconomic–financial interlinkages (e.g., predictors 1, 3, 4, 6, 8, 9), representing the most set of `best` covariates. Furthermore, socioeconomic and health status also cover an important role in this context emphasizing strong causal relationships with some development indicators (e.g., predictors 10, 14, 16).

According to these results, three key factors to address an interdisciplinary analysis of economic growth can be designed. `(i)` Current health expenditure (predictor 14), higher labor productivity (predictor 6), and employment opportunity (predictor 10) would implement outcomes of various health- and finance-related planning policies such as healthier and safer workplaces (predictors 1, 3). In this way, a better and more active workforce for individuals with specific risk factors—such as obesity and social participation—can be designed (see, for instance, Pacifico 2022a). `(ii)` Environment source in terms of energy efforts would positively affect economic growth and other development indicators (e.g., predictors 3, 9, 22, 24, 25). However, they should be handled carefully by displaying a CPS at the center of the range. `(iii)` Financial indicators are the main drivers of spillover effects across countries and sectors (e.g., predictors 4, 8, 9), and their sudden change—whether through being unobserved or badly managed—would negatively affect economic growth (structural breaks).

Concerning the field of socioeconomic and health sources, it is important and has to be accounted for, mainly when dealing with quality of life and risk factors. Indeed, they face many methodological weaknesses, most of which stem from their insufficiently developed theoretical framework. Most of these studies believe that research on quality of life and individual–specific risk factors should be turned away from composite indicators because of serious methodological inconsistencies or should be constructed a list of clear indicators of well-being and workplace (see, e.g., Diener and Suh 1997; Michalos 1997 and Saltelli 2007). The empirical results addressed in this study find evidence concerning the need to highlight a set of potential covariates affecting a country's productivity, and then design a monitoring system for the cross-country socioeconomic–environmental report.

The field of macroeconomic–financial variables is being sufficiently developed both in theoretical and applied issues of indicators' use. More precisely, the use of indicators has been successfully integrated into the theoretical model of business cycles. Thus, most recent studies highlighted a finite set of indicators linked to certain economic phenomena. These relationships were used to explain the observed values of an indicator, and then facilitate the understanding of causal relationships among the indicators' outcomes and certain economic phenomena (see, for instance, Banbura et al. 2010; Bernanke et al. 2005; Canova and Ciccarelli 2016; Carriero et al. 2015, 2016; Ciccarelli et al. 2018; Clark and Ravazzolo 2015; Dees et al. 2007; Pacifico 2019, 2020a). All of these issues have been successfully involved and assessed in this study.

Last but not least, environmental science–in terms of environmental impact–also manages to translate its main concerns to specific methodological frameworks of indicators' use. In this context, recent studies have selected a set of indicators in the environmental policy context based on their operational utility, without focusing on their methodological contribution to exploit empirical approaches evaluating business cycles and related economic indicators. In other words, both fields have to be managed by connecting theory with the corresponding indicators' practice, and formulating the latter for the benefits of an empirical interdisciplinary perspective (see, e.g., Faber 2008; Kroll 2011; Lawn 2003; Neumayer 2000 and Sirgy 2011). Let the hierarchical framework and the open robust shrinking procedure be adddressed in this study, the set of the `best` selected indicators supports either theoretical or practical statements.

The final suggestion highlighted in this study would be to better define and clarify theory and empirical issues which could be implicit in an interdisciplinary research analysis. It would facilitate more fruitful implementations and contributions for future approaches. Overall, interdisciplinary research in financial econometrics would require not only the claims of an empirical case study, but also the language and concepts embedded within the research process. More precisely, instead of focusing on the construction of composite indicators that cover different areas of knowledge, interdisciplinary empirical issues should be based on the identification of key indicators and their linkages through appropriate computational approaches, dealing with complex mathematical-statistical relationships and high dimensionality.

4. Concluding Remarks

This paper improves statements and findings developing an interdisciplinary empirical research in development economics and financial econometrics. Methodologically, a multicountry time-varying Bayesian compressed regression model is used to select the `best` subset of predictors affecting economic growth. Causal relationships and linkages are also investigated in the shrinking procedure to better understand empirical results based on business cycles and related economic indicators. Every relationship is evaluated dealing with potential volatility changes affecting macroeconomic and social indicators. A dynamic investigation is addressed through multivariate conjugate informative mixture priors and MCMC algorithms.

An empirical example is developed by accounting for a large set of macroeconomic–financial and socioeconomic–health variables to perform policy issues and implications. The estimation sample accounts for 43 country-specific models covering the period from March 1990 to December 2020. All data come from OECD and Eurostat databases.

From a modeling perspective, socioeconomic–health indicators and macroeconomic–financial factors hold a relevant position when studying dynamic feedback such as cross-country spillover effects. From a policy perspective, macroeconomic–financial, health, and environmental indicators should be performed in the fields of quality of life, workplace safety, and economic sustainability.

Funding: This research received no external funding.

Data Availability Statement: OECD and Eurostat Statistics.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A. Data Collection

Table A1 displays all `best` final predictors included in the subset $\mathcal{E}$.

Table A1. Data.

Variable (Label)	Description
`use`	Energy use (kg of oil equivalent per capita).
`import`	Energy net imports (% of energy use).
`int`	Individuals using Internet (% of population).
`weig`	Weighted income per capita: National Accounts.
`rdexp`	Expenditure on R&D: Enterprises Survey.
`obe`	Overweight: Aspects of Daily Life Survey.
`cult`	Cultural interests: Aspects of Daily Life Survey.
`socio`	Social participation: Aspects of Daily Life Survey.
`pover`	Risk of poverty: 'EU-SILC' Survey.
`hexp`	Current health expenditure (% of GDP).

Table A1. *Cont.*

Variable (Label)	Description
fcons	Final consumption expenditure (% of GDP).
growth	GDP per capita growth (annual %): $ln\left(\frac{GDP_t - GDP_{t-1}}{GDP_{t-1}}\right)$.
gdp	GDP per capita, PPP (current international $ in logarithm).
gfcf	Gross fixed capital formation (% of GDP).
hexports	High-technology exports (% of manufactured exports).
infl	Consumer price index (%).
pop	Total population age (15-above).
popg	Population growth (annual %).
rpop	Rural population (% of total population).
upop	Urban population (% of total population).
emp	Employment to population ratio (%).
lab	Labour force (% of population).
ppjob	Poorly paid job: Labour Force Survey.
gexp	Exports of goods and services (% of GDP).
imp	Imports of goods and services (% of GDP).
trade	Trade (% of GDP).
prod	Real GDP per capita.

All data refer to OECD and Eurostat databases.

Notes

1. `Best` stands for the model providing the most accurate predictive performance in all candidate models.
2. The PMPs denote the probability of each candidate model in fitting the data.
3. In Bayesian analysis, they refer to the probability that a variable is `in` the model.
4. For further specifications, refer to Pacifico (2022b).
5. Let the test statistic have a particular case of the usual F-test, this is sufficient so that such an effect occurs to reject the null of no significance.

References

Angrisani, Luigi, Antonella Santonicola, Paola Iovino, Antonio Vitiello, Kerin K. Higa, Jacques Himpens, Henry Buchwald, and Nicola Scopinaro. 2018. Ifso worldwide survey 2016: Primary, endoluminal, and revisional procedures. *Obesity Surgery* 28: 3783–94. [CrossRef] [PubMed]

Arellano, Manuel. 2003. *Panel Data Econometrics*. New York: Oxford University Press.

Banbura, Marta, Domenico Giannone, and Lucrezia Reichlin. 2010. Large bayesian vector autoregressions. *Journal of Applied Econometrics* 25: 71–92. [CrossRef]

Barro, Robert J. 2003. Determinants of economic growth in a panel of countries. *Annals of Economics and Finance* 4: 231–74.

Baum, Charles L., and William F. Ford. 2004. The wage effects of obesity: A longitudinal study. *Health Economics* 13: 885–99. [CrossRef] [PubMed]

Bernanke, Ben, Jean Boivin, and Piotr Eliasz. 2005. Measuring monetary policy: A factor augmented vector autoregressive (favar) approach. *The Quarterly Journal of Economics* 120: 387–422.

Black, Jennifer L., and James Macinko. 2008. Neighborhoods and obesity. *Nutrition Reviews* 66: 2–20. [CrossRef]

Blanchard, Olivier J., and Danny Quah. 1989. The dynamic effects of aggregate demand and supply disturbances. *American Economic Review* 79: 655–73.

Böckerman, Petri, John Cawley, Jutta Viinikainen, Terho Lehtiäki, Suvi Rovio, Ilkka Seppälä, Jaakko Pehkonen, and Olli Raitakari. 2019. The effect of weight on labor market outcomes: An application of genetic instrumental variables. *Health Economics* 28: 65–77. [CrossRef]

Borenstein, Severin. 2015. A microeconomic framework for evaluating energy efficiency rebound and some implications. *Energy Journal* 36: 1–21.

Bowsher, Clive G. 2002. On testing overidentifying restrictions in dynamic panel data models. *Economics Letters* 77: 211–20. [CrossRef]

Briassoulis, Helen. 1997. Sustainability indicators. a critical review of the literature. *Topos* 12: 55–75.

Brownson, Ross C., Debra Haire-Joshu, and Douglas A. Luke. 2006. Shaping the context of health: A review of environmental and policy approaches in the prevention of chronic diseases. *Annual Review of Public Health* 27: 341–70. [CrossRef] [PubMed]

Canova, Fabio, and Matteo Ciccarelli. 2009. Estimating multicountry var models. *International Economic Review* 50: 929–59. [CrossRef]

Canova, Fabio, and Matteo Ciccarelli. 2016. Panel vector autoregressive models: A survey. *Advances in Econometrics* 32: 205–46.

Canova, Fabio, Matteo Ciccarelli, and Eva Ortega. 2012. Do institutional changes affect business cycles? *Journal of Economic Dynamics and Control* 36: 1520–33. [CrossRef]

Canova, Fabio, and Fernando J. Pérez Forero. 2015. Estimating overidentified, nonrecursive, time-varying coefficients structural vector autoregressions. *Quantitative Economics* 6: 359–84. [CrossRef]

Carriero, Andrea, Todd E. Clark, and Massimiliano Marcellino. 2015. Bayesian vars: Specification choices and forecast accuracy. *Journal of Applied Econometrics* 30: 46–73. [CrossRef]

Carriero, Andrea, Todd E. Clark, and Massimiliano Marcellino. 2016. Common drifting volatility in large bayesian vars. *Journal of Business and Economic Statistics* 34: 375–90. [CrossRef]

Cawley, John. 2015. An economy of scales: A selective review of obesity's economic causes, consequences, and solutions. *Journal of Health Economics* 43: 244–68. [CrossRef]

Choi, Changkyu, and Myung H. Yi. 2009. The effects of the internet on economic growth: Evidence from cross-country panel data. *Economics Letters* 105: 39–41. [CrossRef]

Ciccarelli, Matteo, Eva Ortega, and Maria T. Valderrama. 2018. Commonalities and cross-country spillovers in macroeconomic-financial linkages. *Journal of Macroeconomics* 16: 231–75. [CrossRef]

Clark, Todd E., and Francesco Ravazzolo. 2015. Macroeconomic forecasting performance under alternative specifications of time-varying volatility. *Journal of Applied Econometrics* 30: 551–75. [CrossRef]

Coveney, John, and Lisel A. O'Dwyer. 2009. Effects of mobility and location on food access. *Health and Place* 15: 45–55. [CrossRef] [PubMed]

D'Acci, Luca. 2011. Measuring well-being and progress. *Social Indicators Research* 104: 47–65. [CrossRef]

Dees, Stephane, Filippo Di Mauro, Hashem M. Pesaran, and Vanessa L. Smith. 2007. Exploring the international linkages of the euro area: A global var analysis. *Journal of Applied Econometrics* 22: 1–38. [CrossRef]

Diener, Ed, and Eunkook Suh. 1997. Measuring quality of life: Economic, social and subjective indicators. *Social Indicators Research* 40: 189–216. [CrossRef]

Dobbie, Melissa J., and David Dail. 2012. Robustness and sensitivity of weighting and aggregation in constructing composite indices. *Ecological Indicators* 29: 270–77. [CrossRef]

Dodson, Elizabeth A., Chris Fleming, Tegan K. Boehmer, Debra Haire-Joshu, Douglas A. Luke, and Ross C. Brownson. 2009. Preventing childhood obesity through state policy: Qualitative assessment of enablers and barriers. *Journal of Public Health Policy* 30: 161–76. [CrossRef]

Dumitrescu, Elena-Ivona, and Christophe Hurlin. 2012. Testing for granger non-causality in heterogeneous panels. *Economic Modelling* 29: 1450–60. [CrossRef]

Faber, Malte. 2008. How to be an ecological economist. *Ecological Economics* 66: 1–7. [CrossRef]

Feldstein, Martin. 1982. Inflation, tax rules, and investment: Some econometric evidence. *Econometrica* 50: 825–62. [CrossRef]

Feng, Jing, Thomas A. Glass, Frank C. Curriero, Walter F. Stewart, and Brian S. Schwartz. 2010. The built environment and obesity: A systematic review of the epidemiologic evidence. *Health and Place* 16: 175–90. [CrossRef] [PubMed]

Fischer, Stanley. 1993. The role of macroeconomic factors in growth. *Journal of Monetary Economics* 32: 485–512. [CrossRef]

Freebairn, David M., and Cheryl A. King. 2003. Reflections on collectively working toward sustainability: Indicators for indicators. *Australian Journal of Experimental Agriculture* 43: 223–38. [CrossRef]

Gahin, R., V. Veleva, and M. Hart. 2003. Do indicators help create sustainable communities? *Local Environment* 8: 661–66. [CrossRef]

Gordon, Robert J. 2002. Does the new economy measure up to the great inventions of the past? *Journal of Economic Perspectives* 14: 49–74. [CrossRef]

Granger, Clive W. J. 1969. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica* 37: 424–38. [CrossRef]

Hadri, Kaddour. 2000. Testing for stationarity in heterogeneous panel data. *The Econometrics Journal* 3: 148–61. [CrossRef]

Hamermesh, Daniel S., and Jeff E. Biddle. 1994. Beauty and the labor market. *American Economic Review* 84: 1174–94.

Handy, Susan, James Sallis, Deanne Weber, Ed Maibach, and Marla Hollander. 2008. Is support for traditionally designed communities growing? Evidence from two national surveys. *Journal of the American Planning Association* 74: 209–21. [CrossRef]

Jesinghaus, Jochen. 2012. Measuring european environmental policy performance. *Ecological Indicators* 17: 29–37. [CrossRef]

Kadiyala, Rao K., and Sune Karlsson. 1997. Numerical methods for estimation and inference in bayesian var models. *Journal of Applied Econometrics* 12: 99–132. [CrossRef]

King, Robert G., and Mark W. Watson. 1992. Testing long-run neutrality. In *Federal Reserve Bank of Chicago*. Working Paper 92. Chicago. Available online: https://www.nber.org/papers/w4156 (accessed on 24 April 2023).

Krajnc, Damjan, and Peter Glavič. 2005. How to compare companies on relevant dimensions of sustainability. *Ecological Economics* 55: 551–63. [CrossRef]

Kroll, Christian. 2011. Different things make different people happy: Examining social capital and subjective well-being by gender and parental status. *Social Indicators Research* 104: 157–77. [CrossRef]

Lawn, Philip A. 2003. A theoretical foundation to support the index of sustainable economic welfare (isew), genuine progress indicator (gpi), and other related indexes. *Ecological Economics* 44: 105–18. [CrossRef]

Lawrence, Roderick J. 2004. Housing and health: From interdisciplinary principles to transdisciplinary research and practice. *Futures* 36: 487–502. [CrossRef]

Levine, Ross, and David Renelt. 1992. A sensitivity analysis of cross-country growth regressions. *American Economic Review* 82: 942–63.

Lütkepohl, Helmut. 1982. Non-causality due to omitted variables. *Journal of Econometrics* 19: 267–378. [CrossRef]

Macintyre, Sally, Anne Ellaway, and Steven Cummins. 2002. Place effects on health: How can we conceptualise, operationalise and measure them? *Social Science and Medicine* 55: 125–39. [CrossRef]

Maurseth, Botolf P. 2018. The effects of the internet on economic growth: Counter-evidence from cross-country panel data. *Economics Letters* 172: 74–77. [CrossRef]

Max-Neef, Manfred. 1995. Economic growth and quality of life: A threshold hypothesis. *Ecological Economics* 15: 115–18. [CrossRef]

McLeroy, Kenneth, Daniel Bibeau, Allan B. Steckler, and Karen Glanz. 1988. An ecological perspective on health promotion programs. *Health Education Quarterly* 15: 351–77. [CrossRef] [PubMed]

McLeroy, Kenneth, Allan B. Steckler, Robert M. Goodman, and James N. Burdine. 1992. Health education research: Theory and practice—Future directions. *Health Education Research* 7: 1–8.

McNeill, Desmond. 1999. On interdisciplinary research: With particular reference to the field of environment and development. *Higher Education Quarterly* 53: 312–32. [CrossRef]

Michalos, Alex C. 1997. Combining social, economic and environmental indicators to measure sustainable human well-being. *Social Indicators Research* 40: 221–58. [CrossRef]

Neumayer, Eric. 2000. On the methodology of isew, gpi and related measures: Some constructive suggestions and some doubt on the 'threshold' hypothesis. *Ecological Economics* 34: 347–61. [CrossRef]

Niemeijer, David, and Rudolf S. De Groot. 2008. A conceptual framework for selecting environmental indicator sets. *Ecological Indicators* 8: 14–25. [CrossRef]

Oreskes, Naomi, Kristin Shrader-Frechette, and Kenneth Belitz. 1994. Verification, validation, and confirmation of numerical models in the earth sciences. *Science* 263: 641–46. [CrossRef]

Pacifico, Antonio. 2019. Structural panel bayesian var model to deal with model misspecification and unobserved heterogeneity problems. *Econometrics* 7: 8. [CrossRef]

Pacifico, Antonio. 2020a. Fiscal implications, misspecified dynamics, and international spillover effects across europe: A time-varying multicountry analysis. *International Journal of Statistics and Economics* 21: 18–40.

Pacifico, Antonio. 2020b. Robust open bayesian analysis: Overfitting, model uncertainty, and endogeneity issues in multiple regression models. *Econometric Reviews* 40: 148–76. [CrossRef]

Pacifico, Antonio. 2021. Structural panel bayesian var with multivariate time-varying volatility to jointly deal with structural changes, policy regime shifts, and endogeneity issues. *Econometrics* 9: 1–35. [CrossRef]

Pacifico, Antonio. 2022a. Obesity and labour market outcomes in italy: A dynamic panel data evidence with correlated random effects. *The European Journal of Health Economics* 1–18. [CrossRef] [PubMed]

Pacifico, Antonio. 2022b. Structural compressed panel var with stochastic volatility: A robust bayesian model averaging procedure. *Econometrics* 10: 28. [CrossRef]

Pesaran, M. Hashem, and Ron Smith. 1995. Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics* 68: 79–113. [CrossRef]

Pilkington, Paul, Marcus Grant, and Judy Orme. 2008. Promoting integration of the health and built environment agendas through a workforce development initiative. *Public Health* 122: 545–51. [CrossRef] [PubMed]

Puhl, Rebecca, and Kelly D. Brownell. 2001. Bias, discrimination, and obesity. *Obesity Research* 9: 788–805. [CrossRef] [PubMed]

Reed, Mark S., Evan D. G. Fraser, and Andrew J. Dougill. 2006. An adaptive learning process for developing and applying sustainability indicators with local communities. *Ecological Economics* 59: 406–18. [CrossRef]

Rooth, Dan-Olof. 2009. Obesity, attractiveness, and differential treatment in hiring: A field experiment. *Journal of Human Resources* 44: 710–35. [CrossRef]

Sallis, James F., Robert B. Cervero, William Ascher, Karla A. Henderson, Katherine M. Kraft, and Jacqueline Kerr. 2006. An ecological approach to creating active living communities. *Annual Review of Public Health* 27: 297–322. [CrossRef]

Saltelli, Andrea. 2007. Composite indicators between analysis and advocacy. *Social Indicators Research* 81: 65–77. [CrossRef]

Sichel, Daniel E. 1999. Computers and aggregate economic growth: An update. *Business Economics* 34: 18–25.

Singh, Rajesh K., Ramalinga H. Murty, Saurabh K. Gupta, and Anil K. Dikshit. 2009. An overview of sustainability assessment methodologies. *Ecological Indicators* 9: 180–212. [CrossRef]

Sirgy, Joseph M. 2011. Theoretical perspectives guiding qol indicator projects. *Social Indicators Research* 103: 1–22. [CrossRef]

Sobal, Jeffery. 2004. Sociological analysis of the stigmatisation of obesity. In *A Sociology of Food and Nutrition: The Social Appetite*, 2nd ed. Edited by John Germov and Lauren Williams. Hoboken: John Wiley.

Stock, James H., and Mark W. Watson. 1988. Variable trends in economic time series. *Journal of Economic Perspectives* 2: 147–74. [CrossRef]

Stokols, Daniel. 1996. Translating social ecological theory into guide-lines for community health promotion. *American Journal of Health Promotion* 10: 282–98. [CrossRef] [PubMed]

Thompson, Robin. 2000. Re-defining planning: The roles of theory and practice. *Planning Theory and Practice* 1: 126–33. [CrossRef]

Turcu, Catalina. 2013. Re-thinking sustainability indicators: Local perspectives of urban sustainability. *Journal of Environmental Planning and Management* 56: 695–719. [CrossRef]

Vecchiarelli, Stephanie, Michael Prelip, Wendelin Slusser, Heather Weightman, and Charlotte Neumann. 2005. Using participatory action research to develop a school-based environmental intervention to support healthy eating and physical activity. *American Journal of Health Education* 36: 35–42. [CrossRef]

Watson, Mark W. 1994. Vector autoregressions and cointegration. *Handbook of Econometrics* 4: 2843–915.
Wooten, James. 2010. Healthy planning in action. *Planning* 76: 20–23.