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DO UNPRICED NATURAL AND ECOSYSTEM CAPITAL AFFECT ECONOMIC OUTPUT? GROWTH REGRESSION ANALYSES

Jang Ping Thia, Jiaqi Su, and Xinyu Kong*

Abstract

Services provided by nature and ecosystem capital are unpriced and their contributions cannot be observed through factor payments. Estimates of nature's GDP contribution are thus based on bottom-up extrapolations of local ecological valuations or various sectoral dependency assumptions. These estimates are hence partial and wide-ranging. On the other hand, omission of nature and ecosystem capital in standard growth regressions potentially biases estimated returns to other factors of production. This paper incorporates various categories of natural capital and biodiversity into growth regressions, with annual data covering more than 100 economies over more than two decades. A range of econometric specifications are used, including fixed effect panel regressions, Arellano and Bond, and Pseudo Poisson Maximum Likelihood. The estimates point to natural capital, especially the narrower and specific ecosystem capital, having a sizeable positive elasticity of around one-third of total gross fixed capital. Ecosystem capital is thus estimated to contribute around USD6–12 trillion (or 10–20 trillion in purchasing power parity terms) annually to the global economy. This estimated contribution is significantly higher than what is implied by existing stock valuations, underscoring the importance of ecosystem capital to sustainable growth.

Keywords: Natural capital; ecosystem; biodiversity; economic growth; sustainability
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* Jang Ping Thia, Lead Economist, AIIB. Email: jangping.thia@aiib.org
Jiaqi Su, Economic Analyst, Economics Department, AIIB. Email: jiaqi.su@aiib.org
Xinyu Kong, Senior Research and Data Assistant, Economics Department, AIIB. Email: xy.kong@aiib.org

1. Introduction

Do unpriced natural and ecosystem capital contribute to economic output and how large might the contributions (if any) be? This paper undertakes a gross domestic product (GDP) growth decomposition exercise with an assembled longitudinal dataset comprising GDP and related national accounts data, as well as more comprehensive measures of natural capital and biodiversity. This expands on traditional growth accounting where GDP is often attributed to human capital, physical capital stocks, and total factor productivity (TFP) only. This paper thus links GDP (a flow concept) to an expanded measure of natural capital and biodiversity, uncovers respective elasticities, and estimates the contribution of natural ecosystem capital to output.

The relationship between economic growth and ecological constraints has long attracted academic and political attention. As early as 1972, the then controversial Limits to Growth report spelt out the challenges of resource depletion and emission, and how these could greatly constrain or even crash growth in the 21st century. More than a decade ago, the Stiglitz, Sen and Fitoussi (2009) Commission also made it clear that GDP was an income flow and would need to account for the damage to the stock of environment wealth in order to drive sustainable development, a point strongly reiterated in the more recent Dasgupta (2021) review. There have been longstanding concerns over how GDP growth could exhaust natural capital to the point of threatening prosperity.

In 2022, the 15th Conference of Parties (COP15) to the Convention of Biological Diversity (CBD) reached the landmark agreement to put 30% of earth under protection by 2030. In 2023, nations agreed to the United Nations High Sea Treaty which would for the first time establish marine protected areas outside national maritime borders.[1] Protecting nature is now seen as central to sustainable development, alongside the net zero transition to avoid catastrophic climate change.

The important link between ecology and economy has also affected economics as a profession. Nature and biodiversity were seen to be outside mainstream economics [Dasgupta (2008)]. This is clearly no longer the case. Though estimates vary, it is now widely acknowledged that nature underpins a significant part of economic activity and human well-being. There has correspondingly been a sea change in data quality for natural capital and biodiversity in recent decades.

The Changing Wealth of Nations (CWON) dataset by the World Bank is one such key effort [World Bank (2021)]. It attempts to capture economies' stock of natural wealth, in addition to man-made physical wealth and human capital. The natural wealth data is further broken down into various components, including nonrenewable natural wealth (fossil fuels, metals, minerals etc.) and renewable natural wealth (timber,

[1] See Convention on Biological Diversity press release, December 19, 2022, "Nations Adopt Four Goals, 23 Targets for 2030 In Landmark UN Biodiversity Agreement." See UN News, June 19, 2023, "Beyond Borders: Why New 'High Seas' Treaty Is Critical for The World."

cropland, fisheries, mangrove, non-timber forest, protected areas etc.).[2] Each iteration of CWON has improved on the previous one and there are efforts underway to improve on the estimates for renewable energy capital.

In this paper, 'ecosystem capital' refers to a narrower subset (mangroves, protected land, non-timber forests) of natural capital, distinguishing it from 'commodity natural capital' (i.e., fossil fuels, metals, minerals etc.) or 'cultivated natural capital' (pastureland, agriculture, fisheries, timber forest). As will be elaborated on later, this distinction is important.

These natural capital estimates also give rise to puzzles. Based on 2018 CWON estimates, the wealth of nations is predominantly in the forms of produced capital and human capital (31% and 64% of total wealth respectively). Commodity capital accounts for a significant part of the remainder. On the other hand, renewable natural capital accounts for only 3% of total wealth. Within this, ecosystem capital wealth is only slightly over 1% of total wealth. These low valuations suggest that ecosystem capital does not contribute much to economic output, which is at odds with numerous studies to be discussed shortly.

Besides the improvement in data on natural capital stock, there are also attempts to derive flow monetary estimates of nature's contributions in both scientific and economics literature. Estimating nature's contributions to economic output is not just an academic exercise. This is important to inform policy and motivate necessary conservation actions.

An approach is based on bottom-up extrapolations. For example, valuations of ecological services are often estimated using local case studies, and these are then extrapolated to some global figures by assuming that similar biomes would offer the same values [see de Groot et. Al (2012); Costanza et al. (2014)]. This approach typically produces rather high global valuations of nature's services. It is estimated that global ecosystem services could be worth as much as USD125 trillion per year (in 2007 dollars).

There are also studies that are based on the sectoral approach. This first assesses how much of each sector's inputs to production are dependent on nature's services or material provisions. This approach then aggregates dependencies at various levels–sector, economy-wide, or global. A United Nations (UN) report states that half of the world's GDP is dependent on nature [UNEP (2021)]. A separate World Economic Forum (WEF) report arrives at a similar proportion [WEF (2020)]. Bottom-up methods tend to result in large estimates because these are typically partial, based on assumptions and extrapolations, and do not typically account for the effects of other factors. Take agriculture as an example—what proportion of output is truly nature-based, as opposed to the contribution of human labor, knowledge, and physical capital

[2] A key use of these data is to allow one to derive net national output measures that account for the loss of natural capital [Dasgupta and Mäler (2000)].

such as farm machinery, warehousing, and logistical infrastructure? Existing work that estimates each sector's dependency on nature are somewhat subjective and partial.[3]

There is also the modelling approach using computable general equilibrium (CGE). Based on CGE modelling, a World Bank study estimates that the collapse of ecosystems will result in USD2.7 trillion lost output per year. This is surprisingly small relative to global GDP compared to the bottom-up approaches. A key reason is that CGE models often build in substitutability between factors of production. In other words, there are possible technological substitutes for nature's services. To be clear, there is often a high degree of uncertainty on how substitutable nature's services can be. While USD2.7 trillion is relatively small, this World Bank estimate does show that certain sectors and poorer economies would be hardest hit with the collapse of nature [World Bank (2021)].

1.1 Contribution of Paper

This paper contributes to these studies by adopting a growth accounting approach, treating natural or ecosystem capital as factors of production. Specifically, we undertake a range of growth regressions to uncover the contribution of nature, even though services provided by nature are unpriced.

As mentioned, we further separate between renewable natural capital into cultivated natural capital and ecosystem natural capital (non-timber forests, protected areas, mangroves). The former is human-modified, while the latter would be much more aligned with nature and biodiversity. This separation is conceptually important as cultivated capital can be at odds with biodiversity. For example, while an increase in agricultural land can contribute to productivity of food production or a rustic environment for well-being, it could also accelerate biodiversity loss. It is thus possible to record a rise in natural wealth and at the same time cause harm to natural ecosystems and species. As is well noted in the growth regression literature, aggregation of distinct factors of production, should they have different marginal products, will lead to biased estimates. The separation between human-modified natural capital and ecosystem capital is thus also important both for conceptual and econometric reasons.

Finally, the paper also leverages on both natural capital and biodiversity data. The research makes use of the Biodiversity Intactness Index (BII), which is based on a geospatially granular assessment of the quality of biodiversity intactness of the environment, aggregated toward a national-level variable (Scholes and Biggs, 2005). The research uses the BII variable essentially to adjust for the quality of ecosystem capital stocks, or, as a separate variable in growth regressions (See Annex A Table 5 for country-specific BII scores.). This is important to ensure that the quality of natural capital is also accounted for. For greater confidence, the regression results of the various approaches are provided for comparison.

[3] World Economic Forum (2020) and PwC score each industry's dependency based on the industry's dependence on identified natural processes.

To preview the results, across all regression specifications, physical and human capital continue to be highly and statistically significant in explaining economies' GDP growth. The results also show that natural capital is important to GDP across all regression settings–and somewhat surprisingly, ecosystem stock is more statistically significant (and economically important) compared to cultivated natural capital or commodity natural capital.

With a range of estimates, we show that ecosystem capital has an elasticity that is around one-third that of total fixed capital stocks (including infrastructure and other gross fixed capital), in contrast to a stock valuation estimate that is fairly low at around 4% of total fixed capital stock only. This is a sizeable impact and provides preliminary evidence that the ecosystem contributes more to economic output than what is implied by ecosystem stock valuation and underscores the importance of maintaining natural and ecosystem capital for sustainable growth.

Section 2 provides a review with the literature. Section 3 provides detailed description of the data sources and the adjustment made. This is supported by further details in two separate Annexes. Section 4 details the regression framework and results. Section 5 discusses the results, to be followed by a short conclusion in Section 6.

2. Review of Literature

We first connect our research to the literature on ecological services. This literature categorizes nature's support to human output and welfare into three broad dimensions. First, nature provides essential "free" or unpriced infrastructure services, such as cleaning water, protecting coastal areas, regulating nutrient cycles, pollinating crops, all of which are critical to so many sectors. Second, nature provides the raw materials and energy for human production and consumption. Agricultural production for example depends largely on land and soil, and construction also draws on naturally occurring materials. The world economy is also heavily dependent on fossil fuels today. Third, nature provides recreational value and welfare to humans. Tourism is perhaps the most pecuniary example (e.g., natural wonders, protected parks, and experiences with wildlife), but the impact of nature on human mental and physiological wellbeing certainly goes well beyond this narrow definition. There is now evidence that birdsongs and nature boost mental wellbeing [Ferraro et al. (2020)].

The recent Dasgupta Review highlights various estimates of the economic benefits of nature and biodiversity, reiterating the importance of sustaining these. Importantly, the interim review also clarifies two related but different concepts—namely nature and biodiversity. "Biodiversity increases Nature's resilience to shocks, reducing the risks to the services we rely on" (Dasgupta, 2020, p. 16). In other words, the review makes it clear that natural capital can be sustained only if there is sufficient biodiversity to support it. Biomass alone is thus not an adequate measure of nature's health.

There have been efforts to account for the economic contribution of nature and ecosystem. Boyd (2006) provides a sketch on what kinds of non-market ecological services should be counted as green GDP, and there are also nascent efforts to compute gross ecosystem product or GEP [Ouyang et al. (2020)]. In some sense, this effort continues to be a work in progress as there will always be some uncertainty around estimates given the complex linkages within nature and with the economy. Such efforts are nonetheless critical to provide a deeper understanding of how nature interacts with the economy, inform policy designs, and motivate actions for conservation.

Four related issues affect natural capital valuation, contribution to GDP and related empirical work. Firstly, natural capital accounting is still relatively new, and methodologies to value natural capital (especially ecosystem capital) are still subject to some uncertainty. For example, it is still debated whether natural capital should be valued using market prices or some form of shadow price. "The use of shadow prices is theoretically obvious . . .The problem is that shadow prices cannot be observed, but a practical approach is followed by starting from market prices (whenever available) and adjusting them for externalities." [Smulders (2012)].[4]

There are also longstanding concerns about the validity of extrapolating valuations from local studies. The key weaknesses have been well articulated. "In practice, it is likely that per-unit demand for non-substitutable services escalates rapidly as supply diminishes, so that simple grossing up of marginal values will probably underestimate total true value. On the other hand, high local values of services such as tourism may not be maintained if extrapolated worldwide." [Balmford et al. (2002)]. In other words, scaling up local valuations could lead to bias in either direction.

This discussion leads to the second issue which is cross-dependency of omitted variables. As briefly discussed, factors of production work together and with nature. Omission of variables in any analysis (including growth regressions) may then cause some assets to pick up the effects of non-measured assets, leading to the wrong valuations. Carse (2012) documents the interesting example of how the Panama Canal in fact relies heavily on the surrounding watershed ecosystem for freshwater to rebalance water levels in the locks for each ship transit.[5] Without the provision of freshwater from nature, there would be low returns to this piece of engineered hard infrastructure. Yet, the provision of water for the canal is largely unpriced, as with most of nature's services. The 2023 drought curtailed the capacity of the canal, reducing the productivity of the asset.[6]

As a national income accounting tool, GDP does not explicitly account for factor payments to nature. It is plausible that natural capital affects the factor returns to other forms of capital (e.g., ecosystems affecting the returns to farm capital, or mangrove

[4] See also inclusive wealth measures (United Nations, 2018). The approach and categories of capital are similar to CWON. The key difference is that CWON relies largely on observed market price (or proxies) to value capital, while the UN inclusive wealth measures rely more on assumed shadow prices.
[5] Around 50 million gallons of freshwater are required for each transit, enough to meet the daily needs of a small-sized city. There are around 30-40 transits per day.
[6] See BBC News. Nov. 1, 2023. El Nino Droughts: Panama Canal Cuts Ship Numbers Further.

protection affecting returns to coastal real estate). Without natural or ecosystem capital being reflected in growth accounting, it is also possible that traditional understanding of the returns to physical and human capital is inaccurate. The returns to other forms of capital, or TFP could be over or understated.

Thirdly, beyond omitted variables, there are also other sources of endogeneity. Consider the effects of depletion. Ecosystem capital may support growth (i.e., a positive relationship), but growth itself may put pressure on the environment and subsequently deplete ecosystem capital—which indeed is the central concern—yielding a negative relationship.

Consider also the endogeneity from measurement. The valuation of mangroves depends on the avoided losses of real estate they protect, but the value of real estate also depends on the protection it receives from mangroves. Furthermore, GDP growth itself will raise asset values and these ‘price effects’ can then also feed into the ‘market valuation’ of natural capital. One can plausibly arrive at a situation where natural capital values increase because of such ‘price effects’ when in reality the underlying quantity or quality of natural capital is being eroded unsustainability. As valuation of capital itself can be endogenous to GDP, it does not provide a true assessment on how GDP depends on such capital. Because of these sources of potentially complex endogeneity, it is actually not clear which sign the ecosystem variable will take with respect to growth.

Finally, there is still a lack of integration between natural capital and biodiversity data. As mentioned, natural capital and biodiversity are related but separate concepts. Thus far, data on biodiversity tends to be narrowly focused and ‘hyper-local’ (e.g., number of species of certain types of flora or fauna in a defined area), and therefore difficult to aggregate. Aggregate natural capital data thus gives rather little information on biodiversity and sustainability, while richer granular biodiversity data (fragmented) provide little clues on biodiversity’s contribution to natural capital or economic output. There have been efforts to aggregate bottom-up biodiversity data into national-level data, one of which will be exploited in this paper as an interaction variable between ecosystem capital and biodiversity.

This paper is also connected to the rich growth accounting literature. Growth accounting has been a standard toolkit for economists to estimate the contributions from various factors of production [see Barro (1999), and Barro and Sala-i-Martin (2004), for comprehensive guides]. Growth accounting has traditionally been used to estimate technological progress as total factor productivity or TFP [Solow (1957)]. Under some assumptions on competitive markets, growth accounting using capital stocks (primal method) is equivalent to that through factor payments (dual method) as clarified by Hsieh (1999).

In the context of this paper, ecosystem services are unpriced and cannot be seen through factor payments. The only feasible approach is to perform a series of regressions using standard capital stocks together with the comprehensive natural capital data. This approach can be robust under some circumstances. Elasticities derived through regressions do not measure the valuation of each factor in the accounting sense, but how much output changes with respect to these capital measures. Hence, even if certain factors are systematically undervalued (in the accounting sense) compared to other forms of capital, elasticity measures can still pick up their true effects on growth.

The growth regression approach is not without its known weaknesses. Should natural capital stocks be measured with large errors (as opposed to just undervaluation), elasticity estimates will suffer from attenuation bias that corresponds to the size of the errors. Nevertheless, one could argue that even attenuated estimates can be useful as lower-bound estimates. As highlighted by Barro (1999), the growth regression approach can be prone to aggregation bias, and also does not work well when there are increasing returns to certain factors. To address this concern, we provide estimates across a range of specifications using various categories of natural and ecosystem capital. We have also separated out infrastructure versus non-infrastructure capital (made possible by the IMF dataset).

As mentioned above, there will be natural concerns over endogeneity. Regression approaches will have to deal with various sources of endogeneity—mismeasurement, omitted variables, and reverse causality. This paper takes a wide-casting approach. Natural capital is first incorporated into a traditional growth regression with country fixed effects. A set of regressions then uses the Arellano-Bond (AB) estimator where endogeneity is treated for using past lagged regressors or other instruments. The last set of regressions uses a Pseudo Poisson Maximum Likelihood (PPML) estimator to better account for heteroskedasticity, in line with more recent literature. In doing so, the paper provides a small innovation that builds on Santos Silva and Tenreyro (2006) to estimate a growth form regression with PPML.

3. Data

The research uses data from several established sources. The Penn World Table (PWT) provides key variables related to economic performance, such as GDP, employment, GDP per capita, and so on. Importantly, the PWT also provides the most comprehensive measure of human capital, which is critical to any growth accounting exercise.[7]

The CWON dataset provides comprehensive data on a range of man-made capital, human capital, and natural capital. As mentioned, most unique for this dataset is the available of natural capital data, spanning both natural renewable capital and natural non-renewable capital. This dataset is also supported by a set of rich technical papers detailing the methodologies behind each of the data items. This research also draws on the IMF capital stock dataset, which contains detailed series on gross fixed capital formation (GFCF).

[7] See Inklaar and Timmer (2013). Version 10, which is used in this analysis, was released in early 2023.

As can be seen from the brief description here, some of the data are provided by more than one dataset. For example, both the PWT and CWON provide estimates of human capital. When such a situation occurs, the choice of which set of data to use is largely down to practical considerations to implement the regressions as robustly as possible.

To give a concrete example, the PWT's human capital index is the rate of return on schooling taken from the literature multiplied by the years of schooling, and then combined with employment data. On the other hand, the CWON uses discounted future earnings, coupled with projected demographic profiles, to arrive at the estimate of an economy's human capital wealth. The latter could be more prone to endogeneity, noting that GDP growth itself can affect earnings. PWT human capital data are also more widely used in the literature. All human capital data used in this research are thus taken from PWT (instead of CWON) to be more in line with the literature.

All three datasets – PWT, CWON, and IMF – provide estimates of fixed capital.[8] Of the three, only the IMF dataset provides further breakdown into public and private sector GFCF, as well as investments through PPPs. This dataset allows private capital and public infrastructure series to be proxied, and for more detailed growth accounting. The PWT capital series, unlike the IMF dataset, does not allow more detailed disaggregation into public, private, and PPP type investments. Hence, the IMF capital stock series are used for this analysis.

3.1 Ecosystem Capital

This research further separates renewable natural capital into two subsets–cultivated capital (timber, cropland, fisheries, pastureland) and ecosystem capital (mangrove, non-timber forest, protected areas). For the avoidance of doubt, this distinction is made for the purpose of this research (i.e., this categorization does not appear in the CWON dataset). It is again important to reiterate that cultivated capital can be at odds with ecosystem and separating the two is conceptually important.

3.2 Accounting for Biodiversity

While CWON provides a good starting point for data on natural capital, it does not include data on biodiversity, which tend to be localized (e.g., count of species at a particular location). However, with more widespread interest in the subject in recent years, there are increasingly more aggregated scores or data available.

Biodiversity Intactness Index

The BII was first started for South Africa [Scholes and Biggs (2005)] and is now extended to global coverage [Newbold et al., (n.d.)]. As the name suggests, this index attempts to measure intactness. It relies on a mix of high-level satellite pictures, field data, and algorithms to create a 0 to 1 score for each granular, spatially differentiated

[8] Note that CWON obtains physical capital stocks from PWT.

area. It is “an estimate of the percentage of original number of specie that remain and their abundance, despite human pressures.” A score closer to 1 will mean greater biodiversity intactness. Coverage has been extended globally and it is now a key data tracked maintained by the Natural History Museum in the UK and used in many research and reports.

The key advantage of BII is that it contains a mixture of granular data, which can then be aggregated at the country level. BII also accounts for both biodiversity and biomass. The slight disadvantage is that this index prizes intactness over relative biodiversity abundance or biomass. For example, a desert may be considered more pristine and achieve a high score, but it may not necessarily have the biomass of flora and fauna compared to a less pristine forest with lower intactness score. It may thus be difficult to compare across regions with vastly different climates and natural environments to begin with. Finally, the latest open source BII data are up to 2014 only, thereby reducing the number of data points whenever this series is used.

Environment Performance Index

The EPI dataset from the Yale Center for Environment Law and Policy uses 40 performance variables to rank countries on their efforts “to protect environmental health, enhance ecosystem vitality, and mitigate climate change” [Wolf et al. (2022)].

The key advantage of this dataset is that with its richer set of 40 variables, it is in principle possible to further unpack the qualitative aspects of nature’s health (e.g., nitrogen management, fisheries health, pollution, waste management, and so on). Unfortunately, this dataset is highly unbalanced.[9] It becomes practically difficult to use these variables consistently to adjust for the quality of ecosystem capital. Nevertheless, where practical, we have used EPI variables as additional instruments in some regressions. The full list of variables used in this paper is provided in Annex A (including other variables in Table 7). In addition, Annex B provides the correlation between BII and various EPI variables, with the relevant EPI variables then selected as additional instruments in one of the regressions (to be explained later).

4. Growth Accounting Regressions

4.1 Growth Model

The paper first illustrates a familiar growth decomposition:

Equation 1

$$Y = K^{\alpha} N^{\beta} (QHL)^{1-\alpha-\beta}$$

[9] Some variables have data collated annually, some once every few years, and some only once in the entire dataset.

Where K and N are infrastructure and non-infrastructure capital stocks respectively, L is labor, H is human capital (HL being effective labor), and Q the augmenting total factor productivity. There is a sizeable literature using the Cobb-Douglas function as the basis for cross country or single growth accounting regressions [see Senhadji (2000), Aghion and Howitt (2007), Chow and Li (2002) etc.].

It is possible to write the above using the more general expression $Y = QK^{\alpha}N^{\beta}(HL)^{1-\alpha-\beta}$.[10] The labor augmenting form has also been used in literature [see Esfahani and Ramirez (2003), Aiyar and Dalgaard (2009), Han et al. (2020)]. Dividing across by HL, the above equation becomes:

Equation 2

$$y = k^{\alpha}n^{\beta}Q^{1-\alpha-\beta}$$

where y, k, n are expressed in effective labor. In growth terms, the equation becomes:

Equation 3

$$\gamma_y = \alpha\gamma_k + \beta\gamma_n + (1-\alpha-\beta)\gamma_Q$$

Where γ_y is the growth rate of output per effective labor (the same analogs hold for other variables with γ). This basic growth accounting model is extended to incorporate natural capital:

Equation 4

$$y = \left(\prod p_i^{\theta_i}\right) k^{\alpha}n^{\beta}Q^{1-\alpha-\beta-\sum\theta_i}$$

Where p_i are the categories of natural capital stocks (again in effective labor) and θ_i the respective elasticities, which in growth terms becomes:

Equation 5

$$\gamma_y = \sum \theta_i p_i + \alpha\gamma_k + \beta\gamma_n + (1-\alpha-\beta-\sum \theta_i)\gamma_Q$$

The above formulation can be represented straightforwardly as a log-differenced regression (e.g., γ_k is represented by $\ln k_t - \ln k_{t-1}$ and so on). Time-invariant variables are also purged, just as it would be under fixed-effect regressions. Growth regressions (as opposed to levels) are also more robust against spuriousness caused by trends.

[10] Barro and Sala-i-Martin (2004) and Jones (2005) show that only the labor-augmenting growth function is consistent with steady-state growth. Note that whether the more general function or the labor-augmenting one used in this paper, the regression estimation will be the same but with a different TFP interpretation arising from intercept.

We will present three sets of regressions. We first show the results from simple fixed effect panel regressions (Table 1). Fixed effect regressions have the advantage of purging any effects of time-invariant cross-country differences. These are also relatively easy to understand and provide readers with the preliminary sense of the estimates. The second set of regressions (Table 2) is based on Arellano-Bond (AB), where past variables are used as instruments to overcome endogeneity. In some specifications, we also include additional instruments from the EPI dataset. The AB estimates should be seen as the benchmark given that these are the most robust to endogeneity concerns. Third, we present a set of regressions that uses PPML estimator as robustness check (Table 3).

4.2 Panel Regressions

This section provides the results of various fixed effect panel regressions. R1 is a traditional growth regression without natural capital (i.e., Equation 3). R2 expands on R1 and includes non-renewable and renewable natural capital as per Equation 4. R3 further disaggregates renewable capital into cultivated capital and ecosystem capital. R4 replaces ecosystem capital with the biodiversity-adjusted one. R5 is similar to R4 but has ecosystem capital and BII as separate variables instead. All regressions are carried out with year dummies, and with clustered standard errors by each economy.

Table 1: Regressions of Output and Capital Stocks

	R1	R2	R3	R4	R5
Infrastructure stock, log difference	0.174***	0.189***	0.177***	0.200***	0.200***
	[0.046]	[0.050]	[0.050]	[0.049]	[0.049]
Other GFCF stock, log difference	0.137***	0.131***	0.129***	0.104**	0.104**
	[0.038]	[0.041]	[0.041]	[0.052]	[0.052]
Non-renewable natural capital, log difference		-0.004**	-0.004**	-0.004**	-0.004**
		[0.002]	[0.002]	[0.002]	[0.002]
Cultivated natural capital, log difference			-0.002	-0.000	-0.000
			[0.011]	[0.011]	[0.011]
Ecosystem natural capital, log difference			0.063**		0.101**
			[0.025]		[0.039]
Renewable natural capital, log difference		0.029*			
		[0.015]			
Ecosystem natural capital BII adjusted, log difference				0.102***	
				[0.037]	
BII, log difference					0.124
					[0.143]
Constant	0.026***	0.026***	0.026***	0.014***	0.014***
	[0.002]	[0.002]	[0.002]	[0.003]	[0.003]
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	2,854	2,476	2,476	1,521	1,521
R-squared	0.151	0.162	0.165	0.197	0.197
Number of groups	125	115	115	113	113
R-Square Overall	0.176	0.188	0.192	0.213	0.212
F-statistics	19.54	19.83	20.54	19.27	18.21
p-value	0	0	0	0	0

Standard errors are clustered by economy and reported in brackets, *** p<0.01, ** p<0.05, * p<0.1
Data sources: Infrastructure and GFCF stocks (IMF), human capital (PWT), BII (Natural History Museum UK), natural capital data (CWON). See Annex A for full details of data sources.

4.3 System Generalized Method of Moments (GMM)

The fixed effect regressions in the previous sub-section provides a preliminary sense of plausible estimates–the combined effects of physical capital (infrastructure and non-infrastructure) are around one-third which is roughly in line with literature [Hall and Jones (1999)]. To further address concerns of endogeneity, a set of regressions using the AB estimator is implemented, where past values of regressors are used as instruments. To be clear, the AB regressions here do not contain lagged dependent variables. Rather, AB is used to address potential endogeneity caused by reverse causality, resting on the assumption what the dependent variable at time t does not affect past regressors, and that past lagged regressors are valid instruments.

The results are presented in regressions R6 to R9, mirroring R1 to R4 respectively. These regressions make use of only system instruments, i.e., lagged values.[11] In regression R10, land area, population, and a set of EPI variables are included as additional instruments (see Table 6 for the list of EPI instruments used and Table 9 on how these correlated with the BII statistic). The assumption here is that these environmental variables correlate and provide information on biodiversity, but do not affect per capita incomes directly.

[11] Roodman (2009) provides a detailed guide on the implementation of system GMM in STATA. The AB regressions are performed using xtabond2 in STATA. This would include two types of past lags as instruments – differenced lags, and level lags.

Table 2: Regressions of Output and Capital Stocks (Arellano-Bond)

	R6	R7	R8	R9	R10	R10(a)
Infrastructure stock, log difference	0.135**	0.220***	0.202***	0.241***	0.221***	0.239***
	[0.060]	[0.045]	[0.045]	[0.052]	[0.044]	[0.082]
Other GFCF stock, log difference	0.149**	0.175***	0.172***	0.145**	0.137***	0.189***
	[0.065]	[0.052]	[0.048]	[0.061]	[0.056]	[0.086]
Non-renewable natural capital, log difference		-0.007***	-0.006***	-0.005**	-0.003	-0.011**
		[0.002]	[0.002]	[0.002]	[0.002]	[0.005]
Renewable natural capital, log difference		0.049				
		[0.033]				
Cultivated natural capital, log difference			0.006	-0.006	-0.002	-0.028
			[0.017]	[0.018]	[0.016]	[0.037]
Ecosystem natural capital, log difference			0.088**			
			[0.040]			
Ecosystem natural capital BII adjusted, log difference				0.083**	0.124***	0.178**
				[0.035]	[0.039]	[0.072]
Constant	-0.021***	0.011**	-0.020***	0.021***	0.01	0.019***
	[0.008]	[0.005]	[0.005]	[0.005]	[0.016]	[0.006]
Instruments	Lagged variables	Lagged variables	Lagged variables	Lagged variables	Lagged variables, land area, population and EPI variables	Lagged variables, land area, population (with collapse)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,854	2,476	2,476	1,521	1,521	1,521
Number of groups	125	115	115	113	113	113
Wald Statistics	738.7	863.9	1090	757	776.7	651.6
P-value	0.000	0.000	0.000	0.000	0.000	0.000
AR(1)	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	0.023	0.022	0.018	0.050	0.048	0.049
Sargan Test	0.000	0.000	0.000	0.000	0.000	0.005
Hansen Test	1.000	1.000	1.000	1.000	1.000	0.600

Standard errors are clustered by economy and reported in brackets, *** p<0.01, ** p<0.05, * p<0.1
Data sources: Infrastructure and GFCF stocks (IMF), human capital (PWT), BII (Natural History Museum UK), natural capital data (CWON). For regression R(10), additional EPI variables are used as instruments. See Annex A for full details of data sources.

For regressions R6 to R10, there are a large number of instruments given the many lags in the dataset. One could constrain the number of lags to reduce the number of instruments, but this treatment would be arbitrary and result in loss of information. The presence of many lag instruments means that the Hansen test of instrument validity will not be informative. Regression R10(a) replicates R10 but without EPI variables instruments, and with the additional collapse function in order to reduce the number of instruments.[12] In R10(a), the BII-adjusted ecosystem variable continues to be significant, with an even higher coefficient. The Hansen test does not reject the validity of instruments.

4.4 Pseudo Poisson Maximum Likelihood (PPML)

Following Santos Silva and Tenreyro (2006), the research checks for the robustness of constant elasticity log linear estimates. This consideration is highly relevant in the context of this paper as there are likely sources of heteroskedasticity–for example, the impact of natural and ecosystem capital could be larger for economies with higher shares of primary sectors (e.g., agriculture). Data on natural capital are also relatively new and subject to various methodological uncertainties.

A key constraint with PPML is that it only deals with non-negative dependent variables. In a growth regression context, this limitation is a particular constraint as growth can be negative in some years. One can thus express growth as a ratio – with a ratio above and below 1 implying positive growth and contraction otherwise. Using t as the time subscript, growth can be written as:

Equation 6

$$\frac{y_t}{y_{t-1}} = \left[\prod \left(\frac{p_{it}}{p_{it-1}}\right)^{\theta_i}\right] \left(\frac{k_t}{k_{t-1}}\right)^{\alpha} \left(\frac{n_t}{n_{t-1}}\right)^{\beta} \left(\frac{Q_t}{Q_{t-1}}\right)^{1-\alpha-\beta-\sum\theta_i}$$

which corresponds to Equation 4. With this expression, negative-value variables are avoided on the LHS, and the RHS variables can be implemented in the PPML estimation as log-differenced terms (e.g., $\frac{k_t}{k_{t-1}}$ on the RHS can be represented by $\ln k_t - \ln k_{t-1}$ and so on), just as the regressors in previous sections. Time-invariant omitted variables would also <u>not</u> have any impact on the regression.

Equation 6 thus allows us to implement PPML to address the concerns arising from heteroskedasticity while retaining key features of earlier growth regressions for comparability.

[12] While it does not reject the null hypothesis of valid instruments, the return of p values of 1 indicates that it is not an effective test. The collapse function generates one moment condition across all lags, as opposed to one moment condition per lag.

Table 3: Regressions of Output and Capital Stocks (PPML)

	R11	R12	R13	R14	R15
Infrastructure stock, log difference	0.173***	0.196***	0.175***	0.199***	0.195***
	[0.045]	[0.048]	[0.049]	[0.050]	[0.044]
Other GFCF stock, log difference	0.137***	0.134***	0.128***	0.101*	0.116**
	[0.039]	[0.042]	[0.041]	[0.054]	[0.050]
Non-renewable natural capital, log difference		-0.004**	-0.004**	-0.005**	-0.004**
		[0.002]	[0.002]	[0.002]	[0.002]
Cultivated natural capital, log difference			-0.002	0.001	-0.002
			[0.011]	[0.010]	[0.010]
Ecosystem natural capital, log difference			0.066***		0.103***
			[0.025]		[0.039]
Renewable natural capital, log difference		0.001			
		[0.014]			
Ecosystem natural capital BII adjusted, log difference				0.105***	
				[0.040]	
BII, log difference					-0.095
					[0.075]
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	2,854	2,475	2,475	1,521	1,626
Number of groups	125	114	114	113	113
chi-square	459.2	540.8	575.3	349.3	402.8
P-value	0	0	0	0	0

Standard errors are clustered by economy and reported in brackets, *** p<0.01, ** p<0.05, * p<0.1

5. Discussions of Results

Natural capital and ecosystem capital stocks are introduced into a standard growth regression framework. This paper argues that such a parsimonious treatment is a strength rather than a weakness. The simplicity allows for comparability with existing estimates in the literature and also for readers to develop an intuitive understanding of the relative magnitudes. Results for a range of specifications are provided to bolster confidence that the key conclusion holds.

Regression estimates show that ecosystem capital has a significant and meaningful economic elasticity of 0.063 to 0.124. In many regressions, the ecosystem capital coefficient is around one-third of the estimated elasticities of physical capital (infrastructure and non-infrastructure combined). These estimates are sizeable, and it becomes clear that ecosystem elasticity estimates are significantly larger than the valuation of ecosystem capital stocks in the CWON dataset.

The standard fixed effect panel (Table 1) and panel PPML regressions (Table 3) show very similar results, while the AB regressions (Table 2) have results in the same direction but with higher coefficients. Though the three sets of regression estimates point to the same general conclusion –namely, the importance of natural or ecosystem capital–the AB estimator would in principle be most robust to endogeneity concerns.

It is clear that with the AB estimator, the coefficients for infrastructure and non-infrastructure GFCF are higher compared to simple fixed effects panel or PPML estimates. Consider simultaneity as the source of endogeneity. Where the dependent variable reverse causes the regressor positively, the general effect is one of attenuation, which is observed here. In other words, the true effect of infrastructure and non-infrastructure on growth is higher once the simultaneity is accounted for in the AB regressions.

5.1 The Importance of Biodiversity and Ecosystem Capital

A subtler point here is that the AB estimator also shows a higher coefficient for the unadjusted ecosystem capital (0.88 in R8 is higher than 0.63 in R3). Recall the 'price effect' discussed in the Introduction. The growth effect on valuation of unadjusted ecosystem is likely positive, and hence detected through this attenuation bias outside of the AB estimator. Importantly, using the BII adjusted ecosystem variable, the estimates are 0.102, 0.083, and 0.105 for fixed effect, AB, and PPML respectively, which are remarkably similar. These are also similar to the AB estimator for non-adjusted ecosystem capital, which is 0.88 in R8.

The conjecture here is that the BII adjusted ecosystem variable is less prone to growth or price effects. While the BII variable is not standalone significant when used separately (as in R5 and R15), the sign for BII is negative. When BII is included as a standalone variable, the coefficients of unadjusted ecosystem capital also become higher at around 0.101 (compared to around 0.63 when BII is excluded).

This finding is perhaps not so surprising in hindsight, as the BII adjusted ecosystem variable by design accounts for depletion (Annex B provides further evidence that BII is negatively correlated to output). The inclusion of BII, whether directly adjusted for ecosystem capital or as a separate variable, gives greater confidence to the estimate of ecosystem capital. All three estimation methods produce similar estimates. Furthermore, the BII adjusted ecosystem variable seems to work well, providing some improvement in the goodness of fit compared to the unadjusted one. The coefficients are also higher than the unadjusted ones. This finding is also informative and highlights the value of making BII adjustments to ecosystem capital.

5.2 Other Natural Capital (Non-Ecosystem)

The growth elasticity of commodity natural capital (i.e., commodities and fossil fuels) is small and mostly negative over the time period of the analysis. It is not to say that commodities and fossil fuels are unimportant for economic output. Indeed, these may even be critical. The interpretation here, given that this is a panel study of economies, is that such endowments have not systematically improved the growth of the endowed economies. This finding is in line with the literature that finds little or even negative impacts of such endowments [Venables (2016); Caselli and Michaels (2013)]. Similarly, cultivated natural capital also has relatively negligible impact on economies' growth.

5.3 The Implication on Factor Contributions

It is important to also discuss what these elasticities imply in terms of factor contributions. Consider the estimates in Table 2. Similar with Han et al. (2020), the elasticity coefficient for infrastructure is also sizeable and larger than non-infrastructure GFCF across all specifications. The combined elasticities of physical capital are around 0.37 in R8 with unadjusted ecosystem capital, and 0.38 and 0.36 respectively adjusted with BII in R9 and R10. These elasticities are broadly in line with the literature, which has often taken the elasticity of all capital to be around one-third though there will be economy-to-economy variations [Hall and Jones (1999)]. This result provides some confidence to the estimates in this paper.

The inclusion of natural or ecosystem capital did result in some changes to the elasticities of infrastructure and non-infrastructure GFCF. Broadly speaking, coefficients for infrastructure capital increased, and coefficients for non-infrastructure GFCF declined or stayed largely unchanged.

Consider omitted variables. The omitted variable interpretation implies ecosystem capital has a negative correlation with infrastructure capital, thus resulting in downward bias of the latter when the former is omitted. The direction of bias for non-infrastructure GFCF is on the other hand less clear cut. This result provides a hint that infrastructure development has indeed compromised natural or ecosystem capital (i.e., negative correlation), underscoring the longstanding concern that large scale infrastructure developments have negatively impacted nature and biodiversity (International Institute of Sustainable Development, n.d.). However, this result does not have to be read as a negative message going forward. Rather, the upshot here is that developing infrastructure in ways to enhance natural ecosystems can in fact boost the returns to infrastructure.

In regression R6 (without natural or ecosystem capital), the combined elasticity of infrastructure and non-infrastructure GFCF is 0.284. Assuming constant returns to scale and that elasticities reflect respective factor payment shares, factor payment to effective human capital is thus 0.716 (this share includes the effects of TFP growth augmenting effective human capital).

In R9, with the inclusion of ecosystem capital and biodiversity, the combined elasticity of infrastructure and non-infrastructure is 0.386, with the ecosystem elasticity at 0.083. With these elasticities, the implied factor share of effective human capital is only 0.531. The interpretation here is that a part of the factor returns to effective human capital is in fact due to unpriced ecosystem services.

5.4 Other Omitted Variables

Omitted variables could also be in the form of institutional quality, which has often been found to affect growth positively. The paper reproduces regression R4 which is simple fixed effect panel, regression R9 which has AB specification and regression R14 based on PPML, with World Bank Governance Variables added as controls for robustness checks. These are not capital stocks in the strict sense but are nonetheless added in this set of regressions as robustness checks. The results are presented in Annex A Table 8. Note that the key result–namely the positive impact of ecosystem capital–continues to hold across these regressions, with a slightly higher elasticity at around 0.12.

5.5 Study Limitation and Future Research

It is worth mentioning that there are also clear caveats to this growth regression exercise. Incorporating natural capital and ecosystems into macroeconomic performance is still relatively new, and so the estimates should be interpreted as preliminary and with caution. In our paper, system GMM is in principle the most robust method against endogeneity, but this method carries known weaknesses as described. Lagged variables are seen as either not sufficiently exogenous or are poor instruments with little information.

Future CWON data revisions would likely incorporate refinements that put greater weight on 'volume' data to estimate natural capital stocks in order to reduce 'price' effects. This improvement could yield more meaningful valuations of natural capital stocks and could reduce potential endogeneity. Future growth regressions to uncover nature's contributions could provide improved estimates. Similarly, work on GEP is nascent but these should in principle provide data on shadow payments to ecosystem services and serve as corroborating data on growth regressions.

The log production function in this paper implies factor substitutability, which is debatable. If there is less substitutability between ecosystem and other forms of capital, there will clearly be a tighter "limit to growth" as natural capital is depleted [England (2000); Meadows et al. (2005)]. We are also unable to address whether there would be a "tipping point" beyond which nature would collapse, and with it a large non-linear negative impact on global GDP.

5.6 Estimated Ecosystem Contribution to GDP

Within the context of this exercise, based on the results here and assuming a global GDP of 164 trillion (in 2022 international purchasing power parity dollars), a conservative elasticity of 0.063 would imply an ecosystem contribution to global GDP of around 10 trillion per year in PPP terms. Using a higher estimated elasticity (0.124), this figure would rise to around 20 trillion in purchasing power parity (PPP) terms. If current USD estimates are used, these would be USD6 trillion to USD12 trillion respectively. The estimates in this paper fall between that of the sectoral approach and CGE modelling, and still point to the substantial contribution of natural capital to prosperity.

6. Conclusion

This paper incorporates various natural and ecosystem capital measures into a traditional growth regression framework and uncovers elasticities that point to the importance of the ecosystem capital. Across many specifications, ecosystem capital elasticity is found to be positive and significant. Ecosystem capital has an effect of around one-third of all physical investment capital (including infrastructure). The contribution of ecosystem to global GDP is sizeable, USD6 trillion to USD12 trillion annually in current USD terms, and 1020 trillion in purchasing power parity terms. This finding also suggests that ecosystem stocks, as they are measured today, are hugely undervalued.

The message of this paper is that ecosystem capital is a key but largely unpriced or undervalued resource important to output and growth. On research, there would need to be further work to measure the contribution of nature to economies and the valuation of such natural and ecosystem capital, and to standardize measurements for cross country comparisons. Over time, it is likely that GEP measurements will be developed for all economies, and GEP would be a major step forward to systematically account for the provisions by nature. As mentioned, the future iterations of CWON will also likely be improved in terms of coverage as well as methodology.

On policy, it is clearly important to channel more resources for the protection and restoration of natural capital and ecosystems to ensure sustainable growth. The United Nations report that financing for nature-based solutions would need to reach more than USD536 billion a year by 2050 represents a four-fold increase from today [United Nations Environment Programme (2021)]. While this required financing may seem large, it is in fact fairly small relative to the contribution of ecosystem capital to global GDP. Seen in the context of the sizeable contribution from nature, this paper also suggests even an accelerated expenditure on nature would still be small relative to its true value and could have high payoffs.

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Annex A Summary of Data

This research makes extensive use of CWON data, summarized in Table 4. It further separates renewable natural capital into two broad categories. Ecosystem capital is defined as the sum of forest (non-timber), mangroves, and protected areas. Cultivated capital is defined as the sum of forest (timber), fisheries, cropland, and pastureland.

Table 4: Summary of CWON Natural Variables

CWON Variable	Remarks	Time Period
	Variables in CWON dataset	
Total wealth	Sum of produced capital, natural capital, human capital, and net foreign assets	1995-2018
Produced capital	Value of machinery, buildings, equipment, and residential and nonresidential urban land	1995-2018
Natural capital	Value of non-renewable natural resources and renewable natural resources	1995-2018
Renewable natural capital	Sum of values of renewable natural resources (forests, mangroves, fisheries, protected areas, cropland, and pastureland)	1995-2018
Forest – timber	Value of timber forest, based on present value of output	1995-2018
Forest – non timber	Value of non-timber forest, based on present value of ecosystem services	1995-2018
Mangroves	Value of mangroves, based on present value of flood protection benefits	1995-2018
Fisheries	Value of fisheries, based on present value of output	1995-2018
Protected areas	Value of protected areas, estimated as the lower of returns to cropland and pastureland	1995-2018
Cropland	Value of cropland, based on present value of output	1995-2018
Pastureland	Value of pastureland, based on present value of output	1995-2018
Non-renewable natural capital	Sum of values of nonrenewable natural resources (oil, gas, coal, and minerals)	1995-2018
Oil	Present value of oil stock	1995-2018
Gas	Present value of natural gas stock	1995-2018
Coal	Present value of coal stock	1995-2018
Minerals	Present value of minerals stock	1995-2018

Source: World Bank

Table 5: BII Scores of Economies (2014)

Antigua and Barbuda	1.000	Botswana	0.825	Lithuania	0.672
Egypt	1.000	Iceland	0.819	Mozambique	0.670
Jordan	1.000	Ethiopia	0.815	Turkmenistan	0.668
Kuwait	1.000	Croatia	0.813	Albania	0.665
United Arab Emirates	1.000	Bolivia	0.805	Paraguay	0.664
Qatar	1.000	Myanmar	0.803	Sri Lanka	0.659
Oman	1.000	Slovenia	0.802	Greece	0.657
Bahrain	1.000	Ecuador	0.801	Thailand	0.655
Iraq	1.000	Chad	0.791	Costa Rica	0.654
Cyprus	1.000	Malaysia	0.785	Italy	0.652
Suriname	0.993	Tanzania	0.784	Comoros	0.652
Cabo Verde	0.990	Tajikistan	0.779	Belgium	0.646
Turks and Caicos Islands	0.979	Panama	0.771	Switzerland	0.643
Saint Kitts and Nevis	0.975	Türkiye	0.770	China	0.634
Algeria	0.967	Namibia	0.770	Nicaragua	0.633
Finland	0.960	Nepal	0.768	Montenegro	0.631
Norway	0.952	Portugal	0.767	Guinea-Bissau	0.629
Central African Republic	0.949	Belarus	0.766	Eswatini	0.627
Sweden	0.949	Georgia	0.766	Kazakhstan	0.625
Curaçao	0.946	Hong Kong, China	0.765	France	0.622
Guyana	0.940	Angola	0.763	Dominican Republic	0.618
D.R. of the Congo	0.940	Brazil	0.762	Czech Republic	0.615
Bahamas	0.940	Yemen	0.753	Guatemala	0.615
Grenada	0.939	Congo	0.748	Philippines	0.615
Brunei Darussalam	0.938	Morocco	0.748	Romania	0.610
Barbados	0.935	Liberia	0.745	South Africa	0.609
Israel	0.931	Mexico	0.741	India	0.606
Trinidad and Tobago	0.913	Kyrgyzstan	0.737	Netherlands	0.605
Equatorial Guinea	0.912	Djibouti	0.733	New Zealand	0.603
Belize	0.908	Austria	0.724	Hungary	0.600
Canada	0.908	Cambodia	0.722	Serbia	0.597
Dominica	0.905	Poland	0.721	Syrian Arab Republic	0.594
Peru	0.902	Honduras	0.721	Ukraine	0.581
Iran	0.898	Colombia	0.720	Madagascar	0.575
Lao PDR	0.896	Bulgaria	0.719	Guinea	0.575
Zambia	0.887	Indonesia	0.719	Togo	0.572
Japan	0.885	Kenya	0.712	Ghana	0.571
Mauritania	0.883	Argentina	0.711	Uganda	0.567
Russia	0.882	Azerbaijan	0.711	Lesotho	0.565
Chile	0.880	Armenia	0.706	Côte d'Ivoire	0.561
Benin	0.877	Sudan	0.701	Lebanon	0.539
Estonia	0.874	Viet Nam	0.697	Sierra Leone	0.534
Mali	0.869	Jamaica	0.697	Luxembourg	0.531
Pakistan	0.868	Bosnia and Herzegovina	0.696	Republic of Moldova	0.508
Venezuela	0.863	Australia	0.696	Mauritius	0.507
Zimbabwe	0.862	Uzbekistan	0.695	Rwanda	0.506
Sao Tome and Principe	0.859	Tunisia	0.693	Mongolia	0.489
Latvia	0.859	Saudi Arabia	0.690	Nigeria	0.474
Burkina Faso	0.856	Spain	0.690	Burundi	0.462
Cameroon	0.855	United States	0.688	Haiti	0.461
Republic of Korea	0.848	North Macedonia	0.687	Denmark	0.449
Niger	0.842	Malta	0.685	United Kingdom	0.423
Gabon	0.840	Germany	0.685	Ireland	0.406
Fiji	0.839	Gambia	0.684	Bangladesh	0.374
Bhutan	0.836	Malawi	0.679	El Salvador	0.371
Senegal	0.829	Slovakia	0.678	Singapore	0.345
				Uruguay	0.332

Source: UNDP and Natural History Museum, UK

Table 6: Summary of Select EPI Variables Used as Additional Instruments in R10

Variable	Time Period
Recycling rate (REC)	2000, 2005, 2010, 2015
Unsafe sanitation (USD)	1995-2019
Nitrogen oxide (NOE)	2002-2019
Methane growth (CHA)	1999-2019
CO2 from land cover (LCB)	2010-2017
PM2.5 exposure (PMD)	1995-2019
Tree cover loss (TCL)	2006-2019
Household solid fuel use (HAD)	1995-2019
Sulphur dioxide exposure (SOE)	2002-2019

Data source: Environment Performance Index by Yale Center of Environmental Law and Policy

Table 7: Other Variables

Variable	Remarks	Time Period
Human capital (H)	Human capital index incorporating education level and return to education. Data source: Penn World Table (PWT)	1995-2019
Employment (L)	Number of persons engaged in employment. Data source: Penn World Table (PWT)	1995-2019
Effective human capital (HL)	Calculated as human capital multiplied by employment by authors	1995-2019
GFCF stock	Calculated as the sum of general government investment and private investment GFCF by authors. Data source: IMF	1995-2018
Infrastructure stock	Calculated as the sum of general government investment (GFCF) and PPP capital stock by authors. Data source: IMF	1995-2018
Population	Data source: United Nations Population Division	1995-2019
Land area	Land area in square kilometers. Data source: FAO	1995-2019
Voice and accountability	Estimate. Data source: World Bank	1996/8, 2000, 2002-2019
Political stability	Estimate. Data source: World Bank	1996/8, 2000, 2002-2019
Government effectiveness	Estimate. Data source: World Bank	1996/8, 2000, 2002-2019
Regulatory quality	Estimate. Data source: World Bank	1996/8, 2000, 2002-2019
Rule of law	Estimate. Data source: World Bank	1996/8, 2000, 2002-2019
Control of corruption	Estimate. Data source: World Bank	1996/8, 2000, 2002-2019

Table 8: Regressions (4), (9) and (14) with World Bank Governance Variables Added as Controls

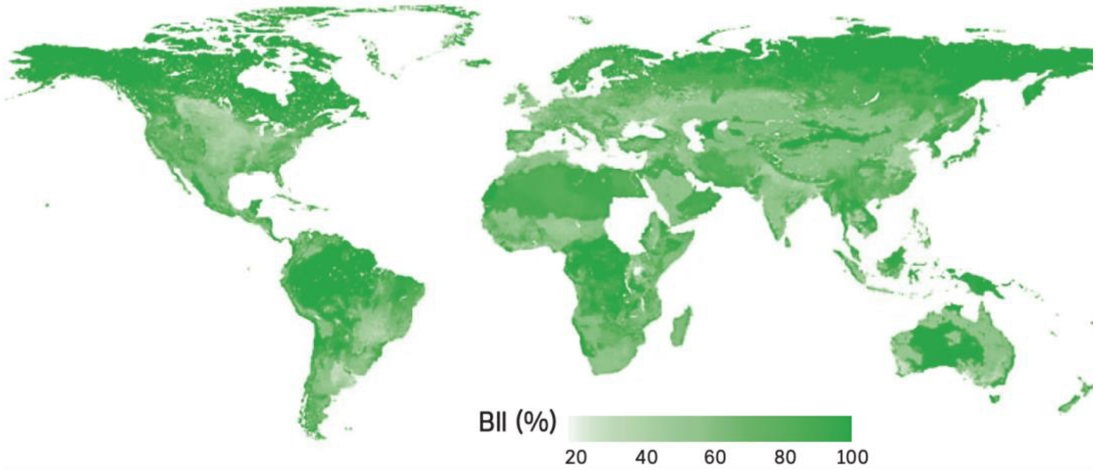
	(4) Annex	(9) Annex	(14) Annex
Infrastructure stock, log difference	0.170***	0.185***	0.174***
	[0.054]	[0.057]	[0.053]
Other GFCF stock, log difference	0.111*	0.145**	0.104*
	[0.059]	[0.059]	[0.062]
Non-renewable natural capital, log difference	-0.004**	-0.003	-0.004**
	[0.002]	[0.002]	[0.002]
Cultivated capital stock, log difference	0.002	0.011	0.004
	[0.010]	[0.016]	[0.009]
Voice and accountability	0.014	0.003	0.008
	[0.016]	[0.004]	[0.016]
Political stability	0.012***	0.003	0.011***
	[0.005]	[0.003]	[0.004]
Government effectiveness	-0.011	0.001	-0.014
	[0.011]	[0.008]	[0.013]
Regulatory quality	0.001	0.006	0.000
	[0.010]	[0.009]	[0.010]
Rule of law	0.004	-0.002	0.005
	[0.013]	[0.009]	[0.012]
Control of corruption	0.012	-0.012*	0.015
	[0.011]	[0.007]	[0.012]
Ecosystem natural capital BII adjusted, log difference	0.124***	0.120***	0.125***
	[0.039]	[0.037]	[0.040]
Constant	0.017***	0.020***	
	[0.003]	[0.006]	
Observations	1,390	1,390	1,390
R-squared	0.197		
Number of groups	111	111	111
R-Square Overall	0.0560		
F-statistics	17.36		
Wald Statistics		989.9	
chi-square			422.3
p-value	0.000	0/000	0.000

Standard errors are clustered by economy and reported in brackets, *** p<0.01, ** p<0.05, * p<0.1

Annex B How BII Correlates with EPI Variables

This Annex provides the correlation of BII with the various EPI variables with a stepwise beta regression using P=0.10 as the cutoff. As described in the paper, the BII provides granular, geospatial assessment of the intactness of natural ecosystems that can then be aggregated at the economy-wide level. A visual sample of BII is provided in Figure 1 below.

Figure 1: Geospatial BII Estimate



Source: Natural History Museum, UK

The BII and EPI differ in significant ways. BII captures the state of ecosystem as it is. EPI captures actionable and measurable outcomes. Take for instance Europe – it ranks high in EPI because it has strong environmental actions but yet its BII is low as it has already lost much of its biodiversity and there is not much more to be exploited. Conversely, some economies in Asia have high BII and are still exploiting such natural resources (e.g., timber) and hence low EPI. The cross-economy correlation between BII and EPI is thus low. BII thus provides an important state variable to adjust for ecosystem wealth, but EPI provides important contextual information.

Within caveats, this exercise provides a further understanding of the detailed factors that have a correlated, or even causal, relationship with BII. This exercise thus provides an important contextual understanding to BII. The relevant EPI variables, together with land area, are then used as additional instruments for BII in regression R10.

The EPI dataset provides 40 performance variables over three broad categories – climate change, environmental health, and ecosystem vitality. For climate change, the variables include emissions of carbon dioxide, methane, greenhouse gas emissions per capita, amongst others. For environmental health, variables include levels of air pollution, use of household solid fuels, sanitation, recycling rate, water safety, solid waste management, etc. For ecosystem vitality, variables include the level of land or marine environment placed under protection, sustainable nitrogen use, strength of species protection, wastewater management, etc. The result of the stepwise regression is provided in Table 9 below. Only variables meeting the cutoff of P=0.1 are displayed.

Table 9: BII Correlation with Economy Characteristics and EPI Variables

Land area, in logs	1.687***
	[0.111]
Per capita GDP in PPP, in logs	-0.471**
	[0.240]
Population, in logs	-0.420**
	[0.197]
Recycling rate	0.022***
	[0.002]
Unsafe sanitation	-0.009***
	[0.003]
Nitrogen oxide exposure	-0.008***
	[0.003]
Methane growth rate	-0.001**
	[0.000]
Carbon dioxide from land cover	0.001**
	[0.000]
PM 2.5 exposure	-0.002*
	[0.002]
Tree cover loss	0.002***
	[0.000]
Household solid fuel use	0.011***
	[0.002]
Sulphur dioxide exposure	0.008***
	[0.003]
Constant	-21.510***
	[1.360]
Year fixed effects	Yes
Economy fixed effects	Yes
Observations	690
chi-square	610546
P-value	0.000

Robust standard errors are reported in brackets
*** p<0.01, ** p<0.05, * p<0.1

Land size is the single most important variable correlated with the BII. Unsurprisingly, population and income (as measured by per capita GDP in PPP) have negative correlations with BII. This finding also underscores why treating for endogeneity is important, as explained in the main paper, as there will be a concern that income growth itself (the dependent variable) is depleting natural or ecosystem capital stocks.

The positive and strong coefficient for recycling shows that economies that have strong recycling practices are also those that conserve the ecosystem. While the sign of the correlation is not surprising, the strength of this variable is a pleasant surprise. Unsafe sanitation has a small negative correlation with BII, providing some hint that investments in infrastructure to provide safer sanitation can positively impact the ecosystem too. Methane growth and particulate exposure (PM2.5) are all unsurprisingly negatively correlated with BII.

A few variables seem to be “wrong-signed” but can be explained by the tension between state of current endowments (which is measured by BII) and actions (which is measured by EPI). Economies with more use of household solid fuels, more exposure to sulfur dioxide and tree cover loss tend to be EMDEs where BII remains relatively more intact but simultaneously present greater opportunities for exploitation (compared to advanced economies). This finding also highlights the need to provide assistance to EMDEs for sustainable development, preserve natural ecosystems, as a global public good.

Data Availability Statement

The data for this research will be made available upon request to the reviewers. We have deposited the research data at an open source depository for replication purposes (https://data.mendeley.com/datasets/cmvw5t56xm/1).