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Can We Keep Growing if We Reduce Our Material Consumption?

Abstract

From the around the 1950s only the consumption of plastic has increased to circa 390 million tons. The constant economic growth and our social standards lead the population to consume more day by day. The genuine question that arises is whether there exists a limit to our consumptions or if the current dependencies of material abuse can be expected to be inverted in the future. By adopting the indicators of Domestic Material Consumption and Material Footprint we have built a regression model, through which answer this existential question and debunk existing and commonly accepted economic relationships like the Kuznets Curve. Our research shows a significant positive linear relation, demonstrating the impossibility of economic growth with a reduction of material consumption.

Introduction

The question of whether economic growth can persist while reducing material consumption is of extreme relevance in today's world, as the constant population and economic growth is critically consuming material resources, endangering our future. For instance, if we consider the surge in plastic usage: In the 1950s, annual global plastic production was around 2 million tons, but by 2022, it has increased exponentially to more than 390 million tons. This research aims to address this pressing question and shed light on this global issue.

Our analysis is based on the interpretation of a cross-sectional dataset of 141 countries, where their real GDP per capita is obtained as an average of the GDP values between 1990 and 2018.We will rigorously test various regression models, paying close attention to their significance levels.We started with a cubic regression, followed by a quadratic and concluded with a linear regression. Each model analysed data on Domestic Material Consumption (DMC), Material Footprint (MF) and GDP per capita expenditure.

Looking into existing literature, it is not possible to determine a commonly accepted thesis on this matter. We can, however, highlight two main schools of thought, the prior sustaining the existence of a positive effect, and the latter a non-significant regression model.

Through our study, we aim to show that the differences in findings stem from the diverse methods utilized. It is crucial to highlight that the regression we are going to present does not account for endogeneity nor for fixed country and time effects, since we are not adopting panel data. Despite these approximations and assumptions we are able to obtain a positive linear estimation. Given this projection, the prospect we face is alarming: the finite resources of our planet may not sustain our increasing demands. The following results are particularly noteworthy as they challenge the widely notorious inverted U-curve hypothesis.

1 - Literature Review

The relationship between economic growth and material consumption has been widely debated in the literature, with a strong emphasis on the *Environmental Kuznets Curves* (EKC) hypothesis. Our focus, in particular, was directed towards the 2019 study of Frank Pothen, Heinz Welsch, "*Economic development and material use. Evidence from International Panel Data*".

1.2 In depth analysis of EKZ

The pivot of this analysis was on two distinct models: the standard EKZ quadratic regression, which claims an inverted U-shaped curve as a result, and a cubic regression, which provided a S-shaped curve, explored by the authors we are referring to. The prior hypothesis suggests that environmental degradation initially increases with economic growth, but once it reaches a certain income level, it begins to decline, thus suggesting the possibility of decoupling economic growth in the context of material consumption from environmental repercussions. The latter hypothesis investigated the use of material across countries with different levels of economic development. This resulted in the Material consumption exhibiting an S-shaped relationship with GDP per capita.

A key aspect of Pothen and Welsh's analysis is the distinction between two critical variables: Domestic Material Consumption (DMC) and Material Footprint (MF). The first focuses on materials used within a country, while the latter accounts for the total materials required to meet domestic demand, including imports. To qualify these relationships, they utilized a regression model, expressed as:

- $ln(\frac{MU_{r,t}}{N_{r,t}}) = \alpha_r + \gamma t + \beta_1 ln(\frac{Y_{r,t}}{N_{r,t}}) + \beta_2 ln(\frac{Y_{r,t}}{N_{r,t}})^2 + \varepsilon_{r,t}$

where $MU_{r,t}$ represents material utilization, either as DMC or MF, $N_{r,t}$ is the population, $Y_{r,t}$is the real GDP, α_r and γ are fixed country and time effects, respectively, and $\varepsilon_{r,t}$ is an error term. '*r*' and '*t*' refer respectively to a country *r* at a specific year, *t*. This model enables the analysis of material use trajectories and provides insights into the potential turning points for economic decoupling. Ideally, it should describe an inverted U-shape pattern[1].

It is important to note that studies have shown that high income nations may externalize material intensive production to lower income countries, which leads to discrepancies between DMC and MF trends. Consequently, we can observe that, while DMC might decline in advanced economies, MF often remains constant or continues to increase, raising doubts about the

[1] Such a pattern is found when the first

sustainability of global resource usage. In addition, the two researchers highlight how there are significant variations when observing countries at different stages of economic development. For instance, they referenced a study from 2003 that found potential EKC patterns in developed nations, suggesting that material use may stabilize or decline after reaching a certain income threshold. Conversely, such patterns are often nonexistent or statistically insignificant in developing nations, where industrial growth drives resource-intensive economic activity. Similarly, it is observed that while developed economies show weak evidence of decoupling, low- and middle-income countries experience a consistent increase in material consumption due to their reliance on resource-heavy industries.

1.3 Different perspectives & personal focus

Expectations on the sign and shape of the curve representing the relationship between GDP and DMC are highly unpredictable, as confirmed also by another research. In 'Natural Resources and Economic Growth: A Meta-Analysis', Tomas Havranek, Roman Horvath and Ayaz Zeynalov explain the heterogeneity of the results in the field. According to their statistics, there has not emerged a unanimous consensus. Empirical papers show 40% of the times a negative relationship, another 40% has found no effect and the last 20%, a positive effect. Furthermore, this research gives us insights on the most commonly used variant of regression function: $G_{it} = \alpha + \beta NAT_{it} + \gamma NAT_{it} \times INS_{it} + \theta X_{it} + \varepsilon_{it}$

where G is a measure of economic growth, NAT is the natural resource richness, INS is the institutional quality, X is a vector of control variables and ε is the error term. '*i*' and '*t*' have the same meaning that *r* and *t* have in the EKZ model's equation.

What really becomes evident is how the results are highly affected and extremely dependent on a multitude of social, geo-political, economic variables concerning matters such as the political stability, the reliance or the abundance on a specific kind of resource or the capital crowding.This is to highlight the volatility of this analysis related to the consideration of the variables implied.

Building on the existing literature, this research aims to evaluate whether global economic growth can persist alongside reductions in material consumption. This will be done through applying the same Frank Pothen and Heinz Welsch's data (GDP per capita, DMC and MF), but turning it into a cross sectional database. We will try to work out our own estimation of the GDP-Material Consumption relation by attempting to develop a forecast of our future environmental and economic prospects and relationships.

2 - Data

2.1 Sources

We gathered our data from an excel table, which was built using a combined set of sources (UN, 'Annualreviews' site, and the university of Groningen). What we are interested in are GDP, Domestic material consumption, and material footprint variables, all expressed as per-capita measurements and rearranged in natural logs.

Data are displayed in a panel format, where each line of the dataset represents a year-and-country observation. Therefore, there are N countries and for each we have t periods observations. The file presents 4 sheets, containing different data organizations. Since we are interested in having the cleanest set possible, we picked our measurements from the '*CleanSample*' collection.

2.2 Structure and Reorganization

We decided to work with cross-sectional data instead of the original panel ones. Consequently we first had to reformat the display in order to obtain a table where each row represents a unique country as an observation, and each column represents the average[2] of the interested variable along all the time periods, for that country. To do so, we coded a script using Matlab.

The code we made extracts first the complete data from the selected sheet and puts them in a table, then it uses two nested-For cycles to build a matrix with the output we seek. The first cycle iterates for the number of unique countries in the dataset, and finds where each country appears[3], then the second cycle follows. It has the peculiarity of cycling horizontally rather than vertically, and builds a row filled with the average values of the variables we need for the country we are referring to in that iteration (the empty cells are not considered in the calculation). After the cycles, we converted the matrix into a table and added the state IDs.

Since one of the studies we've based our research on makes differences not only between material accounting measures but on the degree of development of the countries too, we built two additional tables, for OECD and non-OECD countries respectively. In addition, we

[2] Since everything is in logs of per capita measurements, we decided to opt for a simple arithmetic average.

[3] We set a one-line instruction that builds a logical index about which rows of the original dataset contain the 'i'-th country. This also accounts for outliers possible absence, since it will simply go over the rows (periods) where that country's observation could not have been reported in the clean sample for outlier cleanup.

extended the time horizon considered by the paper by 10 years, taking into account observations up to 2018 (Pothen, Welsch, 2019).

2.3 Descriptive Data

Descriptive statistics for each variable have been organized in tables, one per sample, as shown below.

Overall sample:

Variable	Mean	Median	StDev	Variance
Avg log DMC pc	18.4237	18.2733	1.6266	2.6459
Avg log MF pc	18.4126	18.2843	1.6135	2.6032
Avg log GDP pc	8.9451	8.9498	1.1613	1.3486

OECD sample:

Variable	Mean	Median	StDev	Variance
Avg log DMC pc	19.2880	19.0931	1.4351	2.0594
Avg log MF pc	19.4205	19.2418	1.4591	2.1288
Avg log GDP pc	10.2849	10.3859	0.4383	0.1921

non-OECD sample:

Variable	Mean	Median	StDev	Variance
Avg log DMC pc	18.1163	17.9587	1.5852	2.5128
Avg log MF pc	18.0541	17.9310	1.5164	2.2996
Avg log GDP pc	8.4685	8.6556	0.9443	0.8918

3 - Estimation, Models & Results

The very first point to address regards the different results we obtained from the use of DMC, first, and MF, then, as independent variables. MF's results are jointly more significant and perceptive for the type of investigation we are carrying out, so they should be the ones to which major recognition should be given.

3.1 Econometric models

Moving forwards with our analysis, the models we built are what matters the most. For each sample (overall, OECD and non-OECD), we built a cubic, quadratic and linear regression for both MF and DMC as dependent variables. Even if the attached code shows linear models first, it is only due to a later logical reordering of the script. All the models have been estimated using heteroskedastic-robust s. errors.

As a matter of fact, we firstly tried to build a cubic model[4], in order to test the same assertions of Pothen and Welsch. What we experienced here is that none of the coefficients seem to be significant, even at relatively low-significance thresholds[5], therefore further deductions about the goodness of fit or shape of the relationship would be meaningless. We then went on by *backward elimination*[6], building and testing a quadratic model, which was also described as a core one, close to the EKZ thesis. Unfortunately, neither quadratic model showed significance. This led to the last kind of model we estimated: the linear one. Linear models appear to be the only to show significant coefficients, thus they also represent the final result for our analysis[7].

Here are the general models we estimated[8] for each sample:

- $ln(\frac{MU_r}{N_r}) = \beta_0 + \beta_1\, avg[ln(\frac{Y_{r,t}}{N_{r,t}})] + \beta_2\, avg[ln(\frac{Y_{r,t}}{N_{r,t}})]^2 + \beta_3\, avg[ln(\frac{Y_{r,t}}{N_{r,t}})]^3 + \varepsilon_r$
- $ln(\frac{MU_r}{N_r}) = \beta_0 + \beta_1\, avg[ln(\frac{Y_{r,t}}{N_{r,t}})] + \beta_2\, avg[ln(\frac{Y_{r,t}}{N_{r,t}})]^2 + \varepsilon_r$

[4] In order to simplify the process' description, models have been described in general and divided by types. That is why we are referring to them with singular nouns.

[5] 5% is the most common significance level. We considered then a coefficient being significant at a 10% level as a low-significant one.

[6] 'Backward elimination' is one of the approaches used for carrying out a *stepwise regression*. The actual stepwise method should be automatic, something that we didn't set. We simply followed its purpose, which is looking at t-stats or F-stats of the model and adding or removing regressors up until significant coefficients are found.

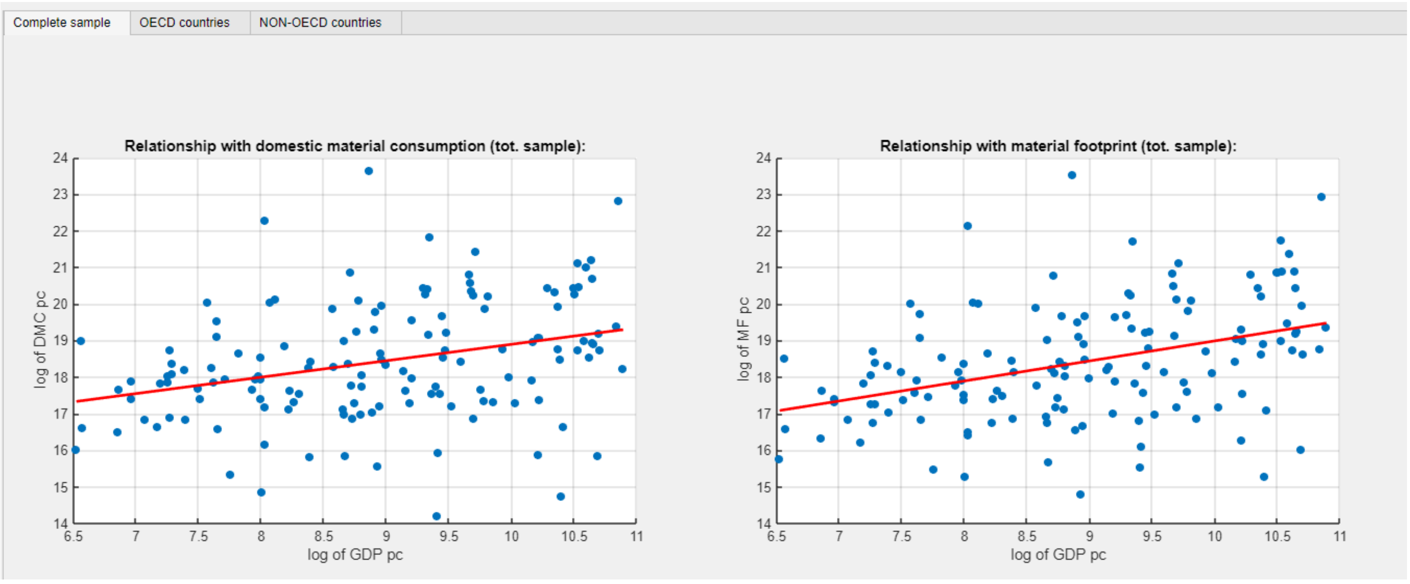
[7] However, finding non-significant relationships should still be considered a result too.

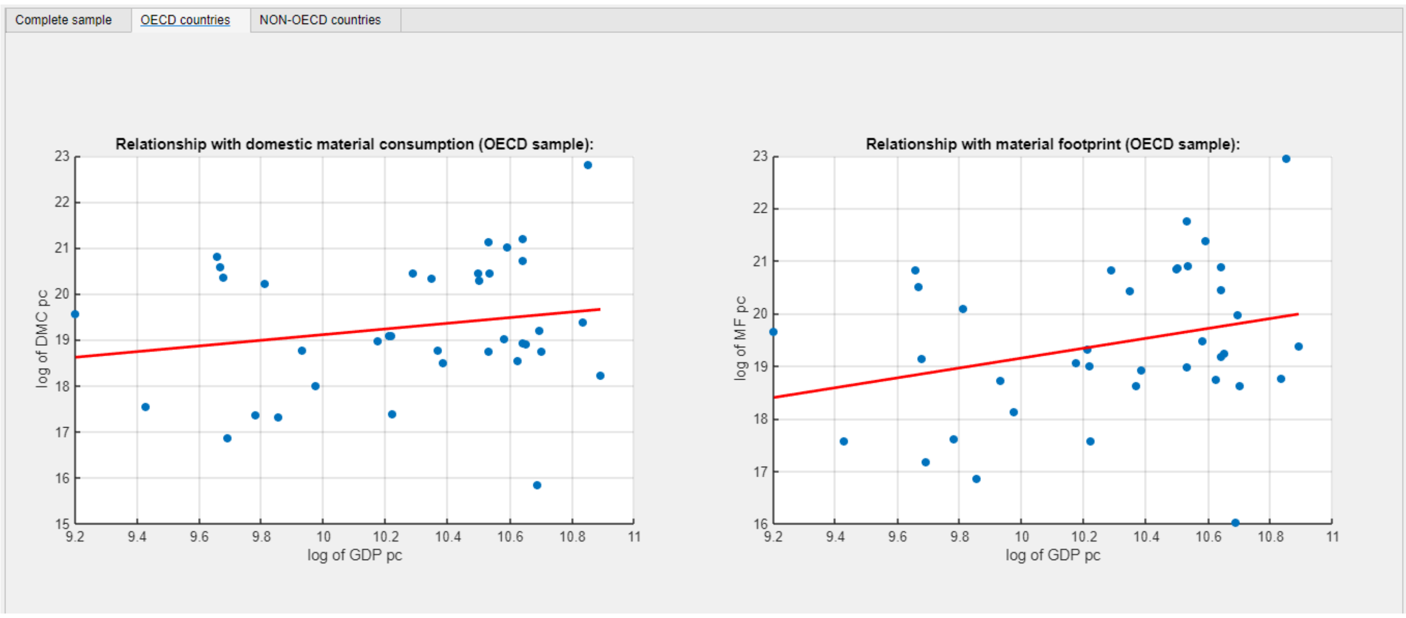
[8] Models maintain the same notation used before, provided by Pothen and Welsch's work (2019). '*Avg*' indicates the arithmetic average.

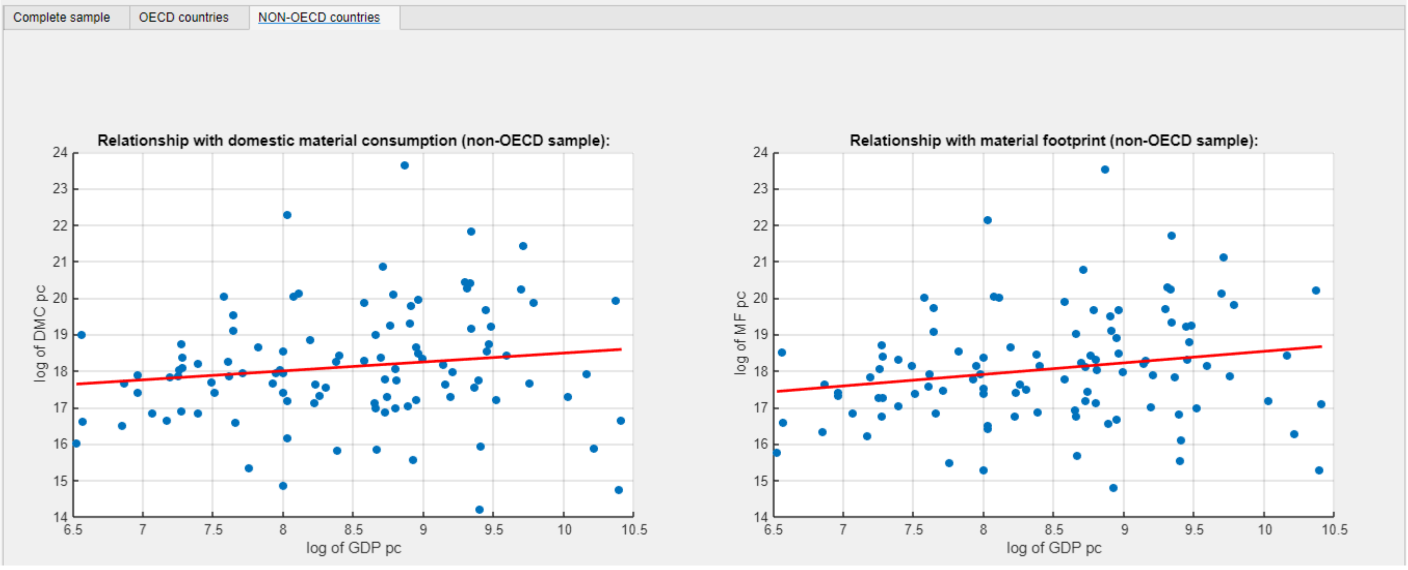
- $ln(\frac{MU_r}{N_r}) = \beta_0 + \beta_1 \, avg[ln(\frac{Y_{r,t}}{N_{r,t}})] + \varepsilon_r$

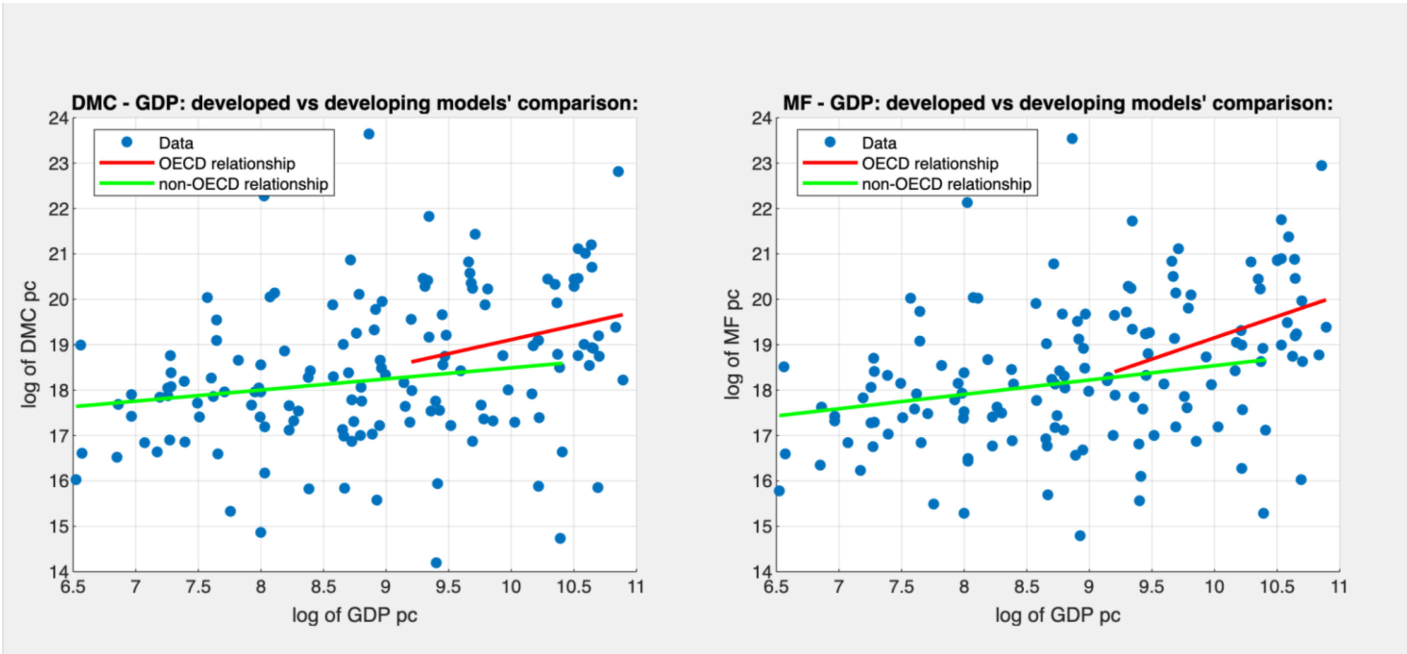
3.1.2 Scatterplots with fitted models

Here are the visual representations of the (significant) relationships we found:









3.2 Results discussions

Complete linear model data follows.

```
Linear overall model for DMC:


White Heteroscedastic Consistent Estimates
Dependent Variable =         DMC
R-squared       =     0.1029
Rbar-squared    =     0.0964
sigma^2         =     2.3908
SER         =     1.5462
F-statistic = 21397.1387
F-test p.value =     0.0000
Durbin-Watson   =     1.9525
Nobs, Nvars     =     141,      2
***************************************************************
Variable      Coefficient      t-statistic    t-probability        VIF
const          14.405436        16.231231        0.000000    -0.000000
logGPDpc        0.449214         4.404578        0.000021     1.000000
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```
Linear overall model for MF:


White Heteroscedastic Consistent Estimates
Dependent Variable =         MF
R-squared       =     0.1550
Rbar-squared    =     0.1490
sigma^2         =     2.2154
SER         =     1.4884
F-statistic = 22727.3653
F-test p.value =     0.0000
Durbin-Watson   =     2.0748
Nobs, Nvars     =     141,      2
***************************************************************
Variable      Coefficient      t-statistic    t-probability        VIF
const          13.519067        15.637868        0.000000    -0.000000
logGPDpc        0.547066         5.512932        0.000000     1.000000
```

```
Linear OECD model for DMC:


White Heteroscedastic Consistent Estimates
Dependent Variable =         DMC
R-squared       =     0.0355
Rbar-squared    =     0.0079
sigma^2         =     2.0432
SER         =     1.4294
F-statistic = 1235.0252
F-test p.value =     0.0000
Durbin-Watson   =     1.7137
Nobs, Nvars     =      37,      2
***************************************************************
Variable      Coefficient      t-statistic    t-probability        VIF
const          12.947747         2.164518        0.037330    -0.000000
logGPDpc        0.616458         1.056620        0.297924     1.000000
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```
Linear OECD model for MF:


White Heteroscedastic Consistent Estimates
Dependent Variable =         MF
R-squared       =     0.0797
Rbar-squared    =     0.0534
sigma^2         =     2.0150
SER         =     1.4195
F-statistic = 1296.1461
F-test p.value =     0.0000
Durbin-Watson   =     1.5567
Nobs, Nvars     =      37,      2
***************************************************************
Variable      Coefficient      t-statistic    t-probability        VIF
const           9.752986         1.688074        0.100290    -0.000000
logGPDpc        0.939975         1.666023        0.104636     1.000000
```

```
Linear NON-OECD model for DMC:


White Heteroscedastic Consistent Estimates
Dependent Variable =         DMC
R-squared       =     0.0212
Rbar-squared    =     0.0116
sigma^2         =     2.4835
SER         =     1.5759
F-statistic = 10527.7638
F-test p.value =     0.0000
Durbin-Watson   =     1.8772
Nobs, Nvars     =     104,      2
***************************************************************
Variable      Coefficient      t-statistic    t-probability        VIF
const          16.044586        11.858523        0.000000    -0.000000
logGPDpc        0.244632         1.473628        0.143661     1.000000
```

```
Linear NON-OECD model for MF:


White Heteroscedastic Consistent Estimates
Dependent Variable =         MF
R-squared       =     0.0388
Rbar-squared    =     0.0294
sigma^2         =     2.2320
SER         =     1.4940
F-statistic = 10721.9599
F-test p.value =     0.0000
Durbin-Watson   =     1.8973
Nobs, Nvars     =     104,      2
***************************************************************
Variable      Coefficient      t-statistic    t-probability        VIF
const          15.375449        12.343642        0.000000    -0.000000
logGPDpc        0.316304         2.078438        0.040179     1.000000
```

As shown by the values we got, everything exhibits a positive trend of material use over GDP growth. Taking into account MF models only from now on, every relation is significant at the

0.05 level, with an exception in the OECD sample, for which we have significance at the 0.1 and 0.15 level. The explanatory power of the models is low, and this could be related to the lack of regressors. Having added some explanatory variables, and/or control ones, sticking with the linear models, could have raised our R^2, however at the cost of possibly raising VIF due to multicollinearity. In addition, it could have also taken the focus away from our starting source's analysis. Another issue to highlight is the manipulation we performed on the data: going from a panel to a cross-sectional table has 'compressed' everything, with an additional 'shrinking' when dividing our main dataset in OECD countries (especially) and non-OECD ones. It is also important to note that the dependent and independent variables used are logarithms, leading to log-log models. This transformation compresses again the scale of the variables in comparison to a level-level model, smoothing out the variability in the data and eventually making the relationships appear more linear. This could also be one of the reasons why we got significance with a linear pattern only.

One of the main claims made by Pothen and Welsch is the difference in results obtained for developed and developing countries (Pothen, Welsch, 2019). Assuming developed countries as the OECD cluster and developing ones as the non-OECD part, we tried to understand if our regressions produced something similar. Even if results are not totally equal, and not fully comparable due to the differences in models and data, we also found that there's actually a difference between the two samples. At low income levels, the OECD group shows a lower reliance on materials than non-OECD, but they demonstrate on the other hand a stronger impact on material consumption over time (greater coefficient). In turn, non-OECD growth seems to impact less on natural resources than the other sample, but exhibits a higher reliance on resources at low income levels. The crossing point between the models of developed and developing nations, representing the estimated income per capita level over which OECD states start to impact more on materials than non-OECD ones, has been calculated inside the code. It appears to be around 8200 dollars (9 circa in log units), a quite high income area. Regarding the overall sample instead, its estimated model positions itself in the middle of the whole estimations.

In the end, we would confidently say that our models, in the way they have been built, lead us to reject both EKZ assumption and cubic-pattern findings of the paper we based our analysis on. What we would affirm is that there is a positive linear relationship between material usage and economic growth, thus making it apparently not possible to grow economically by reducing material depletion in our world.

Conclusions - procedure & data issues

Our analysis confirms a positive relationship between GDP growth and material usage. By addressing the central question of this research, we affirm that economic growth, as measured by GDP per capita, correlates with increased material consumption. However, the reliability of our findings is constrained by methodological choices and data limitations. Nevertheless, despite reducing the exponent degree of the regression and calculating the simple linear regression for the overall sample, we managed to obtain a significant positive estimation for both the GDP per capita and MF relation, and for the GDP per capita and DMC relation. This might suggest that as GDP per capita increases, so as the nations get wealthier, they generally tend to have proportionate growth in material consumption due to more resource-intensive lifestyles. In particular, we notice that the slope for the GDP - MF relation is steeper than the slope for the GDP - DMC relation, where the DMC growth is slower relative to GDP growth, sign of a 'decoupling' effect, probably due to the fact that high-GDP nations tend to outsource their productions and move to a more service-oriented economy.

Let's now consider the distinction in OECD and non-OECD countries. While we do not have strong significance in the regression between DMC and GDP per capita for both groups, we obtained different levels of significance for the MF and GDP relation.

For OECD countries, the relationship between resource use and income could be imagined as less strong than non-OECD ones, due to technology accessibility, policy matters, and other characteristics. Factors that might determine a stronger relationship in developing countries could be related to the industry-centered and resource intensive economy of the developing non-OECD countries. To sum up, OECD countries should exhibit a lower reliance on materials over their growth due to the increasing attention and awareness on environmental and resource issues and their attempts to reduce their material footprint.

However, when examining our OECD and non-OECD models, the results may appear contradictory. In fact, what we got indicates that developed nations tend to rely more on materials than developing ones, apart from low income levels. This result, consistent or not, is probably due to estimation decisions, data treatments and statistical procedures, rather than real-world scenarios. Summarizing, the main biases could come from the numerous omissions, endogeneities and the usage of a cross section rather than a panel dataset. Indeed, computing our regression, we incurred several statistical difficulties concerning endogeneity. Among the causes we have definitely the omission of relevant variables which may give rise to different consumption patterns like country size, climate or also natality. Our model might also appear biased because of the possible correlation between the error term and the explanatory variable: as a matter of fact, we could obtain various accurate material use indicators from diverse levels of GDP. Another crucial issue that is likely affecting the level of bias of the model is correlated to the fact that the dependent and explanatory variables are likely affecting each other simultaneously.

To overcome the issues of endogeneity discussed above, we could have adopted an instrumental variable. This approach, however, is not straightforward. Our dependent variable, material consumption, and our independent variable, GDP per capita, have plenty of common casualties. The majority of the variables considered, like political instability, natality or geographic location of the country would have led to backdoor paths instead of their closure. We believe that these implications quite reflect the general literature on the matter, where there is clearly visible difficulty in agreeing on a common conclusion, whether that might be linear, quadratic, cubic or even existing.

To conclude, the positive linear relation between the GDP per capita and MF excludes any possibility of economic growth when reducing our material consumption. Furthermore, we can expect catastrophic consequences for our society if we maintain our current growth rate or if we can't exploit new momentarily unknown natural resources or develop new technologies, which could slow down resource depletion.

Sources

1. Pothen, F., & Welsch, H. (2019). Economic development and material use: Evidence from international panel data. World Development, 115, 107–119. (https://doi.org/10.1016/j.worlddev.2018.06.008)

2. Pothen, F., Welsh.H (2018) Economic development and material use.

(https://www.sciencedirect.com/science/article/abs/pii/S0305750X18301992)

3. Havránek, T., Horváth, R., Irsova, Z., & Rusnák, M. (2016). Cross-country heterogeneity in intertemporal substitution. CESifo Working Paper No. 2016_03. (https://www.econstor.eu/bitstream/10419/174170/1/wp_2016_03_havranek_et_al.pdf)

4. International Resource Panel. (n.d.). Global material flows database. (https://www.resourcepanel.org/global-material-flows-database)