Nitrogen Surplus Displays a Spurious Environmental Kuznets Curve in Germany

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Abstract

We examine the relationship between nitrogen surplus per hectare and the median monthly wage per capita considering the Environmental Kuznets Curve (EKC) theory. The EKC hypothesizes an inverse U-shape relationship between environmental pollution and per capita income. We use a novel panel data set for nitrogen surplus as an environmental pollutant and a measure of the median monthly wage per capita during the period from 1999 to 2018 for 401 counties in Germany. Our estimation results show that nitrogen surplus displays a spurious EKC in Germany. It is spurious because the inverse U-shape relationship of nitrogen surplus and median wage is rejected by almost all model specifications and by tracing of individual county paths. This implies that in Germany economic growth has not cleaned up the environmental damage from nitrogen surplus. The affected counties remain in a spatial cluster (shown with the individual county paths) that they cannot break out of in the course of the EKC, at least not without political intervention.

Keywords

Environmental Kuznets Curve (EKC); nitrogen surplus; Germany

1 Introduction

The Environmental Kuznets Curve (EKC) postulates an inverted U-shaped relationship between pollution and per capita income. The EKC assumes that pollution increases with rising income in conjunction with economic growth up to a certain threshold value (turning point), after which pollution decreases with rising per capita income. The Kuznets Curve is named after KUZNETS (1955) who originally postulated that income inequality first increases and then decreases with economic development. GROSSMAN and KRUEGER (1991, 1995) and PANAYOTOU (1993) pioneered research on the EKC; since then, it has become the main approach in economics to study the relationship between pollution and economic growth (STERN, 2017).

The EKC is an important indicator for environmental policy and follows a reverse logic to the one put forth in the *Limits to Growth* (MEADOWS et al., 1972), given that the EKC postulates an inverted U-shape relationship between economic growth and the environment (GROSSMAN and KRUEGER, 1995) and not its limitations. This suggests that after a turning point, environmental improvement towards greater sustainability is likely through higher willingness to pay for environmental quality and lower opportunity costs for environmentally friendly production through technological innovation, structural change, environmental regulation, and education (PASTEN and FIGUEROA, 2012) instead of environmental degradation due to limited resources.

The academic evidence on the presence of an EKC is mixed. STERN (2004, 2017) provides two literature reviews about EKC studies. He takes a rather critical stance on the theoretical and empirical studies linked to the EKC. The presence of an EKC is often rejected in country comparison studies but becomes more relevant at smaller scales and for specific pollutants (e.g., SONG et al., 2008; PASTEN and FIGUEROA, 2012; PAUDEL and POUDEL, 2013). The pace of environmental improvement crucially depends on a region's existing position on the EKC (ZHANG et al., 2015). Countries usually referred to as "developing" by mainstream economists, therefore, often have monotonically rising curves, while EKCs are more common in the so-called "developed" countries (STERN et al., 1996; STERN and COMMON, 2001; PASTEN and FIGUEROA, 2012). Despite the efforts taken to estimate EKCs at country level, DASGUPTA et al. (2002) points out that the underlying mechanisms and possible regional heterogeneity are hardly discussed in empirical investigations, possibly leading to imprecise policy recommendations.

The results of the EKC literature for the specific pollutant of nitrogen show a clear empirical relationship; however, theoretical explanations for this relationship are largely missing (e.g., DASGUPTA et al., 2002). At local scale, PAUDEL and POUDEL (2013) find significant coefficients for income and income polynomials for nitrogen, measured as the sum of

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Kjeldehl and nitrate plus nitrite weighted for each county in the US state of Louisiana using data from 1985 to 1998. The authors compare parametric and nonparametric models and find parametric estimation to be suitable for nitrogen. LI et al. (2016) confirm the presence of EKCs for nitrogen, phosphorus, and pesticide indicators in China by applying dynamic panel data models for data from 1989 to 2009. Similarly for India, SINGH and NARAYANAN (2015) find a nonlinear relationship between per capita income and per hectare of agrochemical use by means of data for the period from 1990 to 2008 for 25 Indian states. At global scale, ZHANG et al. (2015) suggest shapes analogous to the EKC for nitrogen pollution from agriculture in many countries of the 113 countries considered from 1961 to 2011 using parametric estimations.

This article extends the existing literature with a study of the EKC for the environmental pollutant of nitrogen surplus considering unique panel data of 401 counties in Germany for the period from 1999 to 2018. We select Germany because the second highest groundwater nitrogen pollution levels in the European Union (EU) are found in Germany (EUROPEAN COMMISSION, 2018: 7).[1] European policies, especially the changes in the Common Agricultural Policy (CAP), the Nitrate and Water Directives, have affected the turning points of EKCs in Europe through supply side reductions of environmental pollutants (see SUTTON et al., 2011a and b; GRINSVEN et al., 2012; GRINSVEN et al., 2015); however, high nitrogen surplus remains in many regions in Germany even though the Fertilizer Ordinance has been amended in 2017 and 2020 towards stricter measures for fertilizer application (KIRSCHKE et al., 2019; HAEUSSERMANN et al., 2020). The European Commission was threatening Germany with a daily penalty of 858,000 Euro if local efforts to combat nitrogen contamination of its water bodies are not enhanced considerably (FRANKFURTER ALLGEMEINE ZEITUNG, 2019; BUNDESMINISTERIUM FÜR ERNÄHRUNG UND LANDWIRTSCHAFT, 2019). In 2022, an agreement was reached between the EU Commission and the newly appointed Minister of Agriculture, Cem Özdemir, that special additional efforts will be made to combat pollution in nitrate vulnerable zones in Germany (DAHM, 2022a, 2022b).

Nitrogen pollution comes at a high cost. The European Union spends roughly 70 billion to 320 billion Euro annually for the consequences of nitrogen pollution (SUTTON et al., 2011a). To the best of our knowledge, there are no previous studies measuring the EKC of nitrogen surplus in Germany. Analysing nitrogen surplus in Germany is, thus, not only of high scientific but also, as just highlighted, of high political importance, not to mention the devastating environmental and health consequences for the affected people. This article will close this research gap.

The findings of this article show that nitrogen surplus displays a spurious EKC in Germany. It is spurious because the estimation results considering different model specifications provide no straightforward results. Therefore, our results do not provide evidence that economic growth in Germany is associated with lower nitrogen pollution. Moreover, tracing the paths of individual counties suggests that the affected counties remain in a spatial cluster from which they cannot break out over the course of the EKC, at least not without political intervention.

The classical framework for explaining the presence of an EKC, as given by PASTEN and FIGUEROA (2012), uses an expansion path of the intersections between utility and production functions, where pollution, in this article nitrogen surplus, is considered as an additional determinant in both functions. The utility function is determined by the willingness to pay for decreasing the marginal pollution or for increasing the marginal quality of the environment. The production function is determined by the opportunity cost for decreasing the marginal pollution or for increasing the marginal quality of the environment. The global goal is to move countries above the turning point (to decrease pollution with increasing economic growth) with policy interventions affecting either the demand or the supply side determinants or both. This macroeconomic reasoning might be useful for understanding global differences of EKCs but fails to provide microeconomic explanations that are crucial for policy making.

The methodology for measuring the EKC, in particular the wrong econometric specification and lack of statistical tests, was criticized. STERN (2004) and COPELAND and TAYLOR (2004) casts doubt on the empirical relevance of several studies, suggesting more rigorous time-series or panel data applications. In particular, the functional form of the parametric panel approaches is subject to criticism. As a result, researchers have begun to make non-parametric estimates to better approximate the real functional forms and compare the non-parametric with the parametric results (PAUDEL et al., 2005; AZOMAHOU et al., 2006;

[1] However, the nitrogen measurement networks of EU countries are not directly comparable triggering a national debate about the issue of comparability at EU level (BACH et al., 2020).

POUDEL et al., 2009; PAUDEL and POUDEL, 2013). The empirical analysis of the EKC on county-level nitrogen surplus in Germany conducted in this article, therefore, uses rigorous panel estimation that includes both parametric estimates, including a first-difference estimate to control for omitted variable bias associated with regional heterogeneity, and non-parametric estimates, as well as relevant statistical tests to overcome the empirical problems identified by STERN (2004, 2017). Moreover, instead of mean per capita income and income level, we use median per capita income and logarithms of wages, respectively, as independent variables, as suggested by STERN (2017). In a second step, we trace the paths of the individual counties over time to better understand the heterogeneity within the counties. Nitrogen surplus of the soil surface budget is calculated from the difference between nitrogen input and output of the utilized agricultural area (UAA) at county level in Germany (see online Appendix A3 based on HAEUSSERMANN et al., 2019 and HAEUSSERMANN et al., 2020).

The article is organized as follows. Section 2 describes the empirical approach used in this article. Section 3 presents the data and provides descriptive statistics. In section 4, we present the estimation and test results. In section 5, we discuss the results in a regional context and in the broader socioeconomic literature and draw conclusions.

2 Estimating the EKC for Nitrogen Surplus in Germany

We use a standard EKC model that uses the CPI adjusted monthly wages per capita and an additional quadratic term of its logarithm to examine the presence of an inverted U-shaped EKC. The model follows the standard structure (STERN, 2004, 2010):

$$N_{it} = a_i + \gamma_t + \beta_1 Y_{it} + \beta_2 Y_{it}^2 + \varepsilon_{it}, \tag{1}$$

where N denotes the nitrogen surplus measured in kilogram per hectare for the different counties and years, and Y stands for the median wage per capita (CPI adjusted, base year 2015). N and Y are both in real numbers and in natural logarithms. i and t are indices of county and year, respectively. a and γ are intercept parameters which vary across counties and years, respectively. ε is the error term. The turning point of monthly wage can be calculated by $\exp(Y^*) = \exp(-\beta_1/(2\beta_2))$.

Based on Equation (1), we estimate fixed-effects models, which use the within regression estimator (e.g., WOOLDRIDGE, 2020). Furthermore, following BECK and KATZ (1995) we also use an approach where ordinary least squares (OLS) parameter estimates are applied, but where the OLS standard errors are replaced with panel-corrected standard errors (PCSE) to control for heteroskedasticity. The PCSE estimator proves to be very accurate and efficient in Monte Carlo simulations and outperforms the OLS estimator when the assumption of homoscedastic errors and/or no serial correlation is violated, but yields similar standard errors to the OLS estimator when the assumptions are not violated (BECK and KATZ, 1995). Furthermore, we use the first difference transformation of the fixed effects model (Equation 1) to remove time-constant unobserved effects to account for possible omitted variable bias due to regional heterogeneity, which potentially affects N:

$$\Delta N_{it} = \beta_1 \Delta Y_{it} + \beta_2 (\Delta Y_{it})^2 + \Delta\varepsilon_{it}. \tag{2}$$

Fixed effects estimation is usually more efficient than first-difference estimation if the ε_{it} are serially uncorrelated; however, if ε_{it} follows a random walk, meaning "substantial positive serial correlation", then first-difference estimation is more efficient given that the difference $\Delta\varepsilon_{it}$ is serially uncorrelated (WOOLDRIDGE, 2020: 467). However, while Y_{it} often shows significant variation in the cross section for each t, the variations of ΔY_i may not be so large (e.g., WOOLDRIDGE, 2020: 442). The parametric panel data model is tested against the nonparametric model (PAUDEL et al., 2005; AZOMAHOU et al., 2006; POUDEL et al., 2009; PAUDEL and POUDEL, 2013) using the DAVIDSON and MACKINNON (1981) approach.

3 Data and Descriptive Statistics

The data structure is a balanced panel of 401 counties over the period from 1999 to 2018.[2] Table 1 provides descriptive statistics and takes into account the panel

[2] The administrative reforms of the counties/city states that took place between 1999 and 2018 in Germany have been considered. For counties/cities that changed their ids and/or names, the old ids/names have been replaced with the new ids/names for all the years considered. The main reforms were those in Mecklenburg-Western Pomerania in 2011 and in Saxony and Saxony-Anhalt in 2008. If several counties were merged to one county, then the time-series of the county that closely followed the time-series trend of the merged county after the reform was used. The counties not considered anymore were dropped from the analysis for all years.

Table 1. Descriptive statistics

Variables		Mean	Std. Dev.	Min	Max	Observations
Nitrogen surplus	overall	72.4	28.3	14.5	192.2	N = 8020
(kg/ha per county)	between		26.0	26.7	148.8	n = 401
	within		11.3	36.5	149.0	T = 20
CPI adj. per capita wage	overall	2856.6	448.3	1759.1	4717.6	N = 8020
(median per county; € per month)	between		437.9	1897.6	4218.3	n = 401
	within		98.5	2284.4	3508.9	T = 20
Year				1999	2018	N = 8020

Note: For the N-balancing, the 401 counties are combined into 299 "district regions" (see HAEUSSERMANN et al. (2019), map on page 72). This compensates for methodological distortions that can occur when calculating the N surplus for small territorial units (usually independent cities) (HAEUSSERMANN et al. (2019): 24; detailed information on pages 70-72).

Source: authors

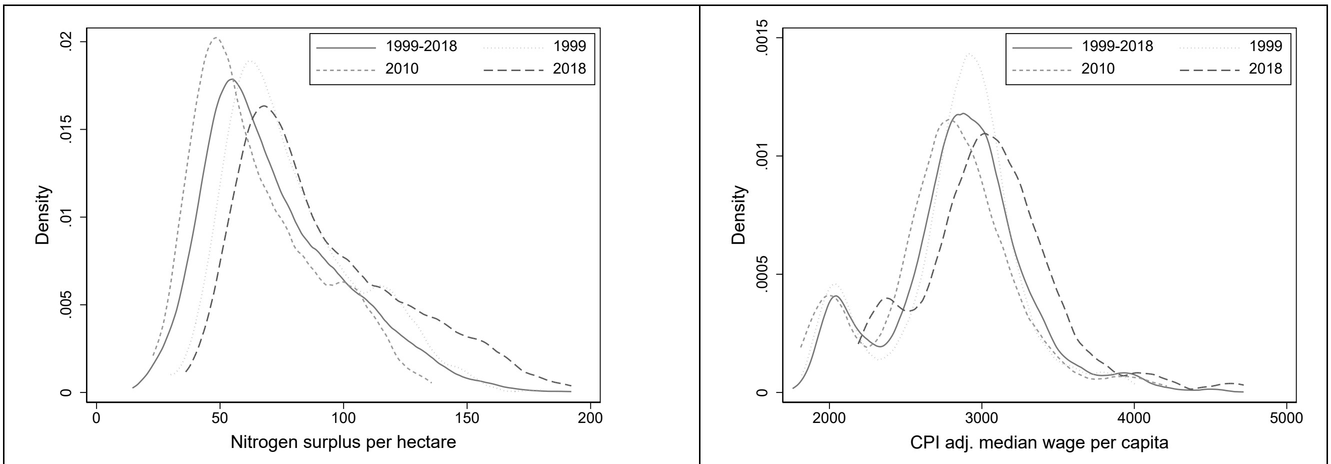
structure of the sample by reporting overall, between and within county magnitudes.

The German Environment Agency provided the nitrogen surplus series, measured in kilogram per hectare (kg/ha) (see online Appendix A3 based on HAEUSSERMANN et al., 2019, and HAEUSSERMANN et al., 2020). The surplus of the nitrogen area balance is used as a central indicator variable to characterise possible water pollution with nitrate from agriculture and its change over time (HAEUSSERMANN et al., 2019). The N-surplus of the area balance corresponds to the difference between the N-inputs and the N-outputs to the agricultural area of the districts during a balance year. The area balance surplus includes the input of nitrogen into the soil without deduction of NH_3 losses occurring during the application of farm manure, digestate and mineral fertiliser on the land, without deduction of N_2, NO_x and N_2O emissions from the soil resulting from nitrification and denitrification (HAEUSSERMANN et al., 2019). Furthermore, the N losses due to the decomposition of organic soil substance in anemic and peatland soils under arable and grassland use are not considered (HAEUSSERMANN et al., 2019). A detailed description of the methodology can be found in online Appendix A3.

The descriptive statistics of N surplus show that nitrogen surplus per hectare varies from 14.5 (the level of Mainz) to 192.2 kg (the levels of Bottrop, Gelsenkirchen, Recklinghausen). The between standard deviation for nitrogen surplus is approximately two times larger than the within standard deviation. Figure 1a shows the Kernel density using the Epanechnikov kernel for nitrogen surplus at the left hand side. It is visible that nitrogen surplus follows a slightly right skewed normal distribution with a long tail in the opposite direction. Furthermore, Figure 1a shows that the extreme values of nitrogen surplus have increased over time. One explanation for this increasing trend could be the additional fermentation residues of biogas plants, which have expanded since the mid-2000s, while the increase in the extreme points could be linked to the transfer of farm manure between regions (see online Appendix A3 for more details).

The Federal Employment Agency provided the median per capita wage series per county, which include the median of the gross monthly per capita wage of full-time employees of the core group, who are subject to social security contributions. GRIMM (2016) provides a detailed description of the methodology used to calculate the median per capita wage. Online Appendix A4 provides a translation of the main methodology applied to calculate the median wage at county level and the methodological changes over time based on GRIMM (2016). A limitation of the data is that the income from self-employment not subject to social security contributions, part-time employment and other income sources are not included. We adjusted the median wage per capita series for inflation (base CPI = 100 in 2015). The descriptive statistics show that the median monthly wage per capita vary from 1,759.1 Euro (Löbau-Zittau) to 4,717.6 Euro (Ingolstadt). The between standard deviation for median monthly wage is approximately four times larger than the within standard deviation. Figure 1b shows the Kernel density estimates using the Epanechnikov kernel for median per capita monthly wage. It is shown that the median monthly wage per capita series follows a normal distribution with some inconsistencies at low median monthly wage per capita levels. Figure 1b also shows that median monthly wage per capita is increasing and that more counties shift to higher median monthly wages over time.

Figure 1. Kernel density estimates for (a) nitrogen surplus and (b) median wage for the period from 1999-2018, 1999, 2010 and 2018 using the Epanechnikov kernel



(a) (b)

Source: authors

4 Results

Tables 2 to 4 in the online Appendix A1 present the estimation results considering different functional forms and samples. Table 2 shows the non-parametric results and the estimation results for the whole sample, covering the years from 1999 to 2018, for both real number and logarithmic form estimates. Table 3 uses the same functional forms but excludes the drought year 2018 as it could potentially bias the results, followed by Table 4, which controls for outliers and excludes nitrogen surplus data that are below 14 kg/ha and above 86 kg/ha. For each sample in Tables 2 to 4, we estimate fixed effects (FE), first differences (D.FE) and panel corrected standard errors (PCSE) models.

4.1 Test Results and Model Fit

At the bottom of Table 2 in online Appendix A1, we report the statistical test results. The Hausman test indicates that the fixed effects panel model is preferred over the random effects panel model. Therefore, we focus on the fixed effects panel model and conduct the relevant tests for cross-sectional dependence, heteroskedasticity, autocorrelation, and stationarity. The Pesaran test finds no cross-sectional dependence in the model. The null of homoskedasticity (or constant variance) is rejected, indicating the presence of heteroscedasticity in the data. The Wooldridge test for autocorrelation shows that the data has no serial correlation. The unit root tests (Levin-Lin-Chu (LLC)) with the optimal lag level chosen by AIC, indicate that both time series have unit roots in most of the specifications considered. However, if we control for cross-sectional correlation by removing cross-sectional means, the LLC test rejects the hypothesis that the series for the logarithm of nitrogen surplus has a unit root. Similarly, the Fisher-type unit-root tests based on the augmented Dickey-Fuller (ADF) tests (CHOI, 2001) with drift and two lags strongly reject the hypothesis that the logarithm of nitrogen surplus and the CPI adjusted median monthly wage series have unit roots. In contrast, the same ADF tests with trend fail to reject the hypothesis that both series contain unit roots. Therefore, the results from the unit-root tests provide no straightforward results.

The R^2 for the models in levels is understood as the amount of time variation in the explanatory variables. In the estimations without year dummy variables, the R^2 is much lower than in the models with year dummy variables. The reason is that in the estimations with year dummy variables, a year dummy variable is included for each year from 1999 to 2017 or 2018 (base year); the 18 or 19 additional year dummies largely increase explanatory power of the respective models (see also WOOLDRIDGE, 2020: 466 on the usually very high R^2 in dummy variable regression). By changing the model through differencing, we also change the total variance for calculating the R^2; therefore, the R^2 in the first difference estimation cannot be directly compared to the models in levels. The R^2 in the first difference specification is usually lower because it eliminates the portion that is explained from the within time variation in the explanatory variables.

4.2 Estimation Results

The results of our estimates are presented in Tables 2 to 4 in online Appendix A1 and the corresponding figures in online Appendix A2. Let us first look at the non-parametric results (Model 0 in Table 2, online Appendix A1; Plot 0 in online Appendix A2). The non-parametric model provides evidence for an EKC as it very clearly shows the inverted U-shaped curve between nitrogen surplus and monthly wages. However, it is based on the assumptions of the Epanechnikov kernel, which is assumed to be symmetric and unimodal density at zero, which can also be seen in the descriptive statistics in Figure 1.

Let us now turn to the results of parametric estimation for different functional forms and samples (see online Appendices A1 and A2). The results from the fixed effects estimations show that most wage coefficients are statistically significant and positive and most wage square coefficients statistically significant and negative. The findings, therefore, provide evidence for an EKC relationship. The Figures 2 and 8 in online Appendix 2 show that there is a downward and thus negative correlation between the nitrogen surplus and wages. The logarithmic function (Figure 8) even shows some evidence for an EKC. However, the results from the fixed effects specification show that the year dummy variables explain most of the variation in the regression. Given that the wage and wage-square coefficients can change significance and magnitude in the fixed effects estimations with the additional year dummy variables, they are most likely correlated with the year dummy variables, possibly linked to unobserved heteroscedasticity and/or unit root issues in the standard errors. We suspect heteroscedasticity and/or a unit root because the test results show neither cross-sectional dependence nor autocorrelation in the time series but reject the homoskedasticity assumption and provide no straightforward results for the unit root tests.

To control for heteroscedasticity in the standard errors, we estimate an OLS model with panel corrected standard errors (PCSE) based on BECK and KATZ (1995). The results from the PCSE estimations mostly confirm the fixed effects estimations. They are consistent across models and show positive wage effects and negative squared wage effects, which is a clear indication of EKCs. However, Figures 6 and 8 in online Appendix A2 show exponentially increasing curves. Using the PCSE approach provides more accurate standard errors, if the standard errors vary from the underlying assumptions in OLS models (homoscedasticity, no serial correlation), but provide standard errors similar to OLS, if the underlying assumptions in OLS models are met (BECK and KATZ, 1995). However, while the PSCSE approach controls for heteroscedasticity and serial correlation in the standard errors, it is not clear how unit roots are addressed with the PCSE.

To take care of the unit root issue, we estimate the first-difference fixed effects model that controls for potential omitted variable bias. The results are mostly opposite to those of the fixed effects estimator and the PCSE estimator, but are mainly not statistically significant and have different magnitudes and signs. Most importantly, the first-difference model suggests negative nitrate inputs, which makes no sense. The largely insignificant results are also reflected in the marginal change in nitrogen surplus, which are strange when looking at the Figures 4 and 10 of the first-difference estimations.

Additionally, we include a cubic term of the logarithm of CPI adjusted wage but the models did not converge; therefore, we have not considered the cubic term in the estimations. The DAVIDSON and MACKINNON (1981) approach finds no conclusive results of whether the parametric or the nonparametric model is preferred.

In this way, our findings on the presence of an EKC for nitrogen surplus, presented in Appendices A1 and A2, are not as clear-cut as suggested by the literature (e.g., LI et al., 2016, for China, PAUDEL and POUDEL, 2013, for Lousiana (US), SINGH and NARAYANAN, 2015, for India) that we discus in the introduction. We conclude that it is not possible to estimate the EKC for the nitrogen surplus considering different counties in Germany for the years from 1999 to 2018, as the first-difference estimates provide insignificant results and non-meaningful marginal effects.

Furthermore, we plot the 401 individual counties for the years from 1999 to 2018 with the logarithm of nitrogen surplus at the y-axis and the CPI-adjusted median monthly wages at the x-axis (see online Appendix A5). The time plots show no evidence for an improvement of nitrogen surplus with additional wage at county level over time. Tracking individual county paths over time provides no evidence of an EKC of nitrogen surplus in Germany and shows that the affected counties remain in a spatial cluster from which they cannot break out over the course of the EKC, at least not without political intervention.

5 Discussion and Conclusion

With this article, we analyse the EKC for the environmental pollutant of nitrogen surplus considering 401 counties in Germany for the period from 1999 to 2018. The reason for choosing Germany is linked to the high groundwater nitrogen pollution levels in the country (EUROPEAN COMMISSION, 2018: 7) and the negative environmental and health consequences for the affected people.

At first glance, following the non-parametric Epanchenikov kernel estimates, there seems to be an observable EKC. However, the first-difference estimates, which we consider most appropriate for considering the unit root problem in the data, reject the existence of an EKC for the nitrogen surplus in Germany. Furthermore, tracking the pathways of individual counties does not provide evidence of county-specific EKCs (see online Appendix A5).

The question arises whether previous studies confirming the existence of EKCs have rigorously accounted for possible omitted variable bias with first difference estimates. We find that this is not the case for most of the studies reviewed in this article; therefore, we follow STERN'S (2004, 2017) critical stance on the theoretical and empirical studies linked to the EKC.

Our results provide evidence that in Germany economic growth has not cleaned up the environmental damage of excessive nitrogen surplus. It seems that the now problematic regions with additional economic growth do not become "better" by an increase in wages. Breaking path dependencies may be the key to reducing the environmental impact of excess nitrogen, although this will require enormous scientific effort to better understand the complexity and interconnectedness of the underlying behavioural, cultural, social, economic, institutional and innovation dynamics.

Looking at the counties with high nitrogen surplus and low wages, the majority are found in many northern and north-western regions as well as in some counties in the south, without any significant improvement in the period considered in our study from 1999 to 2018. These counties are also the main regions of cattle husbandry in Germany, located mainly in Schleswig-Holstein, Lower Saxony and Bavaria (see AGETHEN, 2019). Due to the high amount of manure, more nitrogen is possibly applied in these counties than the crops are able to absorb and convert into biomass (WILKE, 2015) even though regional transfers of manure have been accounted for (HAEUSSERMANN et al., 2019; HAEUSSERMANN et al., 2020). For example, in Northwest Germany, pig and poultry farming is concentrated, in particular in the Oldenburger Münsterland (TAMÁSY, 2014), where approximately 120,000 hectares of agricultural land is missing for providing appropriate fertilization (phosphate) or a regulatory allocation (nitrogen) of the regionally occurring nutrients (LWK, 2013). The nutrient requirement of the available area is, thus, in an obvious disproportion to the nutrient accumulation from animal husbandry and biogas plants (TAMÁSY, 2014). A similar situation can be observed in Bavaria. The Bavarian State Office for the Environment (LFU, 2019) reports that nitrogen, which the crops can no longer utilize, is discharged from the soil as surplus and can be found, for example, as nitrate in the groundwater and can cause diverse negative effects on the natural balance, such as acidification, eutrophication, water pollution and impairment of biological diversity (e.g., nutrient inputs from agricultural activities in the Altmühl river (MEHDI et al., 2015)).

Parallel to the dynamic development of livestock farming, a large number of traditional medium-sized enterprises developed in the upstream and downstream sectors from slaughterhouses to meat processing plants. In total, approximately a third of the employees subject to social insurance contributions in the Oldenburger Münsterland in 2012 worked in the so-called "Agribusiness-Clusters", especially in slaughterhouses and meat processing (TAMÁSY, 2014: 205). The German meat industry is characterised by relatively low wages and a precarious employment situation associated with subcontracting to workers from Eastern Europe (TAMÁSY, 2014; Wagner and HASSEL, 2016). This provides evidence for a complex interlinkage of ecological and social issues linked to nitrogen overuse in intensive livestock production.

Based on our results, as already highlighted, we make the claim that there is not enough evidence in favour of an EKC for nitrogen surplus in Germany. Economic growth can, thus, not clean up the environmental damage caused by nitrogen surplus. The most affected regions that are mainly located in the northern, north-western, and southern areas of the country are best advised to employ additional local measures to combat nitrogen surplus alongside the official regulations (e.g., CAP, Nitrate Directive, Water Directive, and Fertilizer Ordinance). From 01 January 2021, Nitrate Vulnerable Zones (Nitratkulissen) have been established in many states and, together with additional institutional and behavioural change as well as sustainable innovation, could bring about positive environmental change.

The scope and regulation of agricultural nitrate pollution has also been a topic of constant debate in the socioeconomic literature. While KANTER et al. (2019) suggest broader considerations of agricultural value chains beyond the farm to tackle nitrate pollution more efficiently, MCGUIRE et al. (2013) focus on farmers' identities for better comprehension. ALMASRI (2007) suggest improved management frameworks to tackle nitrate contamination by applying multi-criteria decision analysis. TODERI et al. (2007) propose participatory approaches that go beyond the mere biophysical modelling to better understand the groundwater pollution issue and to provide local solutions. CASTRO CAMPOS (2022) proposes the Rules-Boundaries-Behaviours (RBB) framework and engaged fieldwork to holistically address farmers' sustainability issues.

In the context of in/formal institutions, many farmers do not seem to believe in the effectiveness of the formal regulations of the Nitrates and Water Directives to protect the environment in Germany; this is shown, for example, by the mass protests of German farmers in January 2020 against the amendment of the Fertilizer Ordinance.[1] Alongside the issue of disbelief, there is a lack of enforcement of formal rules that can trigger noncompliant behaviors (e.g., HELMKE and LEVITSKY, 2004). In the case of nitrate water contamination, it is simply not possible to directly control the timing and frequency of fertilizer application of each individual farmer or contracted workers through formal institutions.

Finally, after discussing potential behavioural and institutional factors, we want to point out the specific data limitations in our study. HAEUSSERMANN et al. (2019, 2020) have already stressed possible weaknesses due to several assumptions and data restrictions for calculating the nitrogen surplus (see online Appendix A3), which also apply to our analysis. Regarding the wage data, the monthly median per capita wage data are limited to the median of the gross monthly per capita income of full-time employees of the core group, who are subject to social security contributions; however, income from self-employment not subject to social security contributions, part-time jobs and other income sources are not included, which could bias the results.

To arrive at a holistic understanding of the links between pollution and economic growth, it would be useful for future studies to take into account the complexity and interconnectedness of the underlying behavioural, cultural, social, economic, institutional and innovative dynamics through participatory approaches.

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Appendix A1. Model Comparison of the Estimation Results of the EKC

Table 2. Estimates of nitrogen surplus, Germany 1999-2018 (full sample)

	Non-parametric estimates	Parametric estimates											
Variables	**Nitrogen surplus**	**Nitrogen surplus[a]**						**Ln nitrogen surplus[a]**					
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		FE	FE	D.FE	D.FE	PCSE	PCSE	FE	FE	D.FE	D.FE	PCSE	PCSE
CPI adj. wage		0.074***	-0.023***			0.136***	0.133***						
		(0.01)	(0.01)			(0.00)	(0.00)						
CPI adj. wage-square		-0.001***	0.001**			-0.001***	-0.001***						
		(0.00)	(0.00)			(0.00)	(0.00)						
D. CPI adj. wage				0.075***	-0.005**								
				(0.00)	(0.00)								
D. CPI adj. wage-square				0.001**	-0.000								
				(0.00)	(0.00)								
Ln CPI adj. wage								2.860	4.431**			37.633***	37.539***
								(4.16)	(1.85)			(1.51)	(1.34)
Ln CPI adj. wage-square								-0.096	-0.298**			-2.347***	-2.344***
								(0.26)	(0.12)			(0.10)	(0.09)
D. Ln CPI adj. wage										2.881***	-0.115		
										(0.19)	(0.08)		
D. Ln CPI adj. wage-square										20.630***	4.050**		
										(6.03)	(1.86)		
Mean													
Nitrogen surplus	72.302***												
	(0.296)												
Effect													
CPI adj. wage	0.004***												
	(0.001)												
Years	No	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Constant		-82.067***	141.489***	-0.349**	23.030***	-135.120***	-111.320***	-12.479	-11.943*	-0.008***	0.307***	-146.578***	-145.768***
		(17.05)	(11.95)	(0.18)	(0.24)	(5.75)	(5.43)	(16.34)	(7.22)	(0.00)	(0.00)	(5.94)	(5.30)
Observations	8020	8020	8020	7619	7619	8020	8020	8020	8020	7619	7619	8020	8020
Adjusted R^2	0.1229	0.090	0.782	0.039	0.903	0.094	0.206	0.084	0.820	0.035	0.913	0.099	0.232

Notes*:* Robust standard errors are in parentheses. Ln refers to logarithm. FE stands for fixed effects. D.FE refers to the first difference fixed effects. PCSE refers to panel corrected standard errors. a) For the models (3), (4) and (9), (10), the first difference of nitrogen surplus and the logarithms of nitrogen surplus is used, respectively. * p<0.10, ** p < 0.05, *** p < 0.010

The test results from the standard fixed effects model are: FE versus RE Hausman test: chi2 (2) = 90.1 (p-value: 0.00), Heteroskedasticity: chi2 (401) = 28360.04 (p-value: 0.00), Autocorrelation (Wooldridge test): F (1, 400) = 1.128 (p-value: 0.2889); Pesaran's test of cross sectional independence: 0.516 (p-value: 0.6055).

Source: authors

Table 3. Parameter estimates of nitrogen surplus, Germany 1999-2017 (excluding the drought year 2018)

Variables	**Nitrogen surplus**						**Ln nitrogen surplus**[a]					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	FE	FE	D.FE	D.FE	PCSE	PCSE	FE	FE	D.FE	D.FE	PCSE	PCSE
CPI adj. wage	0.075***	-0.010			0.140***	0.136***						
	(0.01)	(0.01)			(0.00)	(0.00)						
CPI adj. wage-square	-0.001***	0.000			-0.001***	-0.001***						
	(0.00)	(0.00)			(0.00)	(0.00)						
D. CPI adj. wage			0.055***	-0.002								
			(0.00)	(0.00)								
D. CPI adj. wage-square			0.000	-0.000								
			(0.00)	(0.00)								
Ln CPI adj. wage							9.824**	5.987***			38.976***	38.506***
							(4.21)	(2.09)			(1.55)	(1.40)
Ln CPI adj. wage-square							-0.566**	-0.399***			-2.435***	-2.407***
							(0.27)	(0.13)			(0.10)	(0.09)
D. Ln CPI adj. wage									2.114***	-0.086		
									(0.19)	(0.08)		
D. Ln CPI adj. wage-square									17.000***	3.585*		
									(6.06)	(1.88)		
Years	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Constant	-67.134***	94.248***	-1.212***	-6.968***	-138.381***	-137.286***	-38.102**	-18.241**	-0.020***	-0.109***	-151.710***	-149.817***
	(15.81)	(11.23)	(0.17)	(0.21)	(5.79)	(5.50)	(16.60)	(8.19)	(0.00)	(0.00)	(6.10)	(5.50)
Observations	7619	7619	7218	7218	7619	7619	7619	7619	7218	7218	7619	7619
Adjusted R^2	0.039	0.786	0.023	0.907	0.096	0.199	0.033	0.812	0.020	0.911	0.099	0.223

Notes: Robust standard errors are in parentheses. Ln refers to logarithm. FE stands for fixed effects. D.FE refers to the first difference fixed effects. PCSE refers to panel corrected standard errors. a) For the models (3), (4) and (9), (10), the first difference of nitrogen surplus and the logarithms of nitrogen surplus is used, respectively. * $p<0.10$, ** $p < 0.05$, *** $p < 0.010$

Source: authors

Table 4. Parameter estimates of nitrogen surplus, Germany 1999-2017 (excluding outliers)

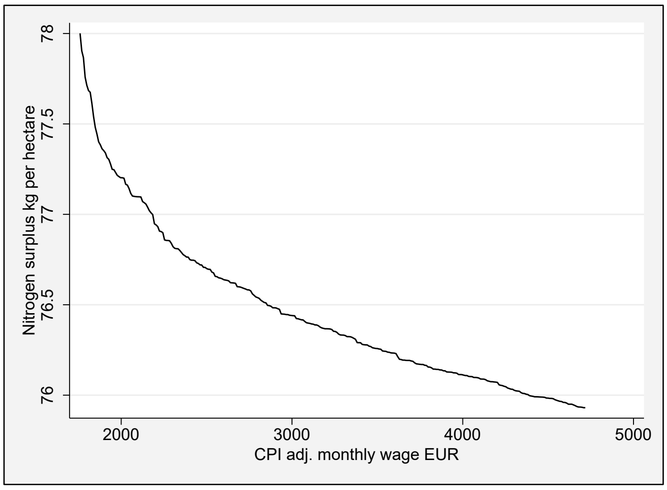
Variables	**Nitrogen surplus**						**Ln nitrogen surplus[a]**					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	FE	FE	D.FE	D.FE	PCSE	PCSE	FE	FE	D.FE	D.FE	PCSE	PCSE
CPI adj. wage	0.075***	-0.010*			0.140***	0.136***						
	(0.01)	(0.01)			(0.00)	(0.00)						
CPI adj. wage-square	-0.001***	0.000			-0.001***	-0.001***						
	(0.00)	(0.00)			(0.00)	(0.00)						
D. CPI adj. wage			0.055***	-0.002								
			(0.00)	(0.00)								
D. CPI adj. wage-square			0.000	-0.000								
			(0.00)	(0.00)								
Ln CPI adj. wage							9.827**	5.989***			38.983***	38.519***
							(4.21)	(2.09)			(1.54)	(1.39)
Ln CPI adj. wage-square							-0.566**	-0.399***			-2.435***	-2.407***
							(0.27)	(0.13)			(0.10)	(0.09)
D. Ln CPI adj. wage									2.138***	-0.078		
									(0.19)	(0.08)		
D. Ln CPI adj. wage-square									16.934***	3.533*		
									(6.05)	(1.87)		
Years	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Constant	-66.860***	94.698***	-1.211***	-6.961***	-138.492***	-137.398***	-38.111**	-18.241**	-0.020***	-0.109***	-151.751***	-149.880***
	(15.77)	(11.14)	(0.17)	(0.21)	(5.79)	(5.49)	(16.60)	(8.18)	(0.00)	(0.00)	(6.08)	(5.49)
Observations	7611	7611	7210	7210	7611	7611	7611	7611	7210	7210	7611	7611
Adjusted R^2	0.039	0.787	0.023	0.907	0.097	0.198	0.034	0.812	0.021	0.912	0.101	0.222

Notes: Robust standard errors are in parentheses. Ln refers to logarithm. FE stands for fixed effects. D.FE refers to the first difference fixed effects. PCSE refers to panel corrected standard errors. a) For the models (3), (4) and (9), (10), the first difference of nitrogen surplus and the logarithms of nitrogen surplus is used, respectively. * $p<0.10$, ** $p < 0.05$, *** $p < 0.010$

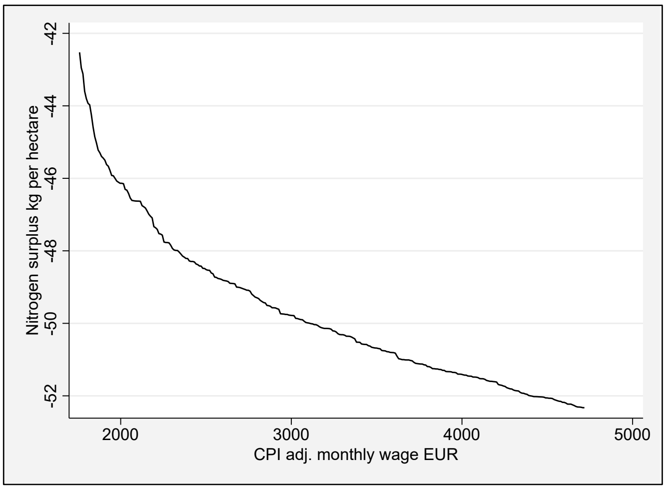
Source: authors

Appendix A2. Figures of Parametric Estimates from Table 4 and Non-Parametric Estimates from Table 2

(0) Non-parametric estimation



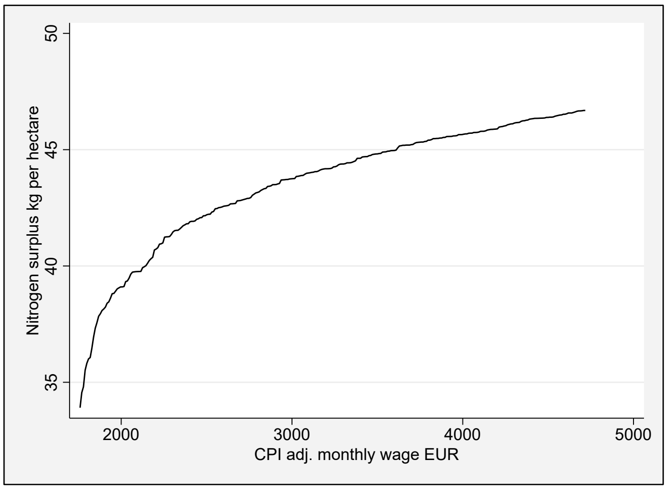
(2) FE with years



(4) D.FE with years

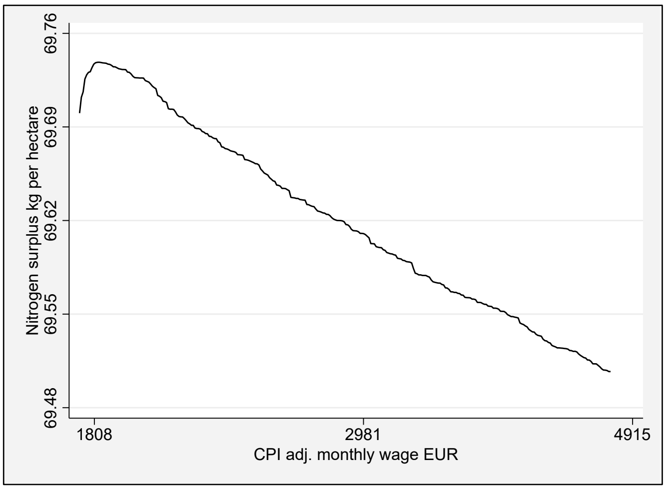
Nitrogen surplus = 94.69845-.0102609*cpi_income +4.37e-07*cpi_income_square

Nitrogen surplus = -6.961112 -.0020986*cpi_income -.0000103*cpi_income_square



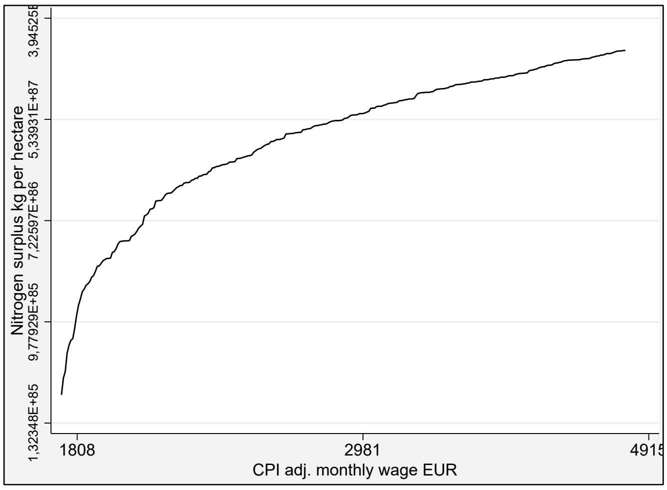
(6) PCSE with years

Nitrogen surplus = -137.3983 +.1362598*cpi_income - .0000221*cpi_income_square



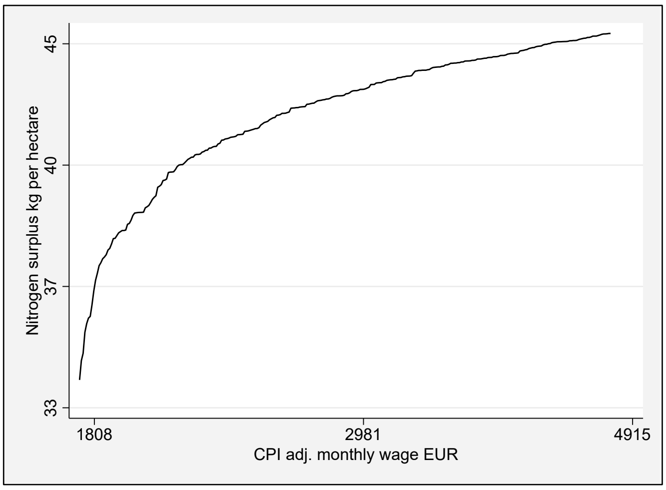
(8) FE with years (logarithm)

Ln nitrogen surplus = -18.2414 +5.988705*ln_cpi_income - .3987419*ln_cpi_income_square



(10) D.FE with years (logarithm)

Ln nitrogen surplus = -.1093291- .0783074*ln_cpi_income+3.532513*ln_cpi_income_square



(12) PCSE with years (logarithm)

Ln nitrogen surplus = -149.8803+38.51888*ln_cpi_income- 2.407474*ln_cpi_income_square

Source for all: authors´ estimations