Price-induced changes in greenhouse gas emissions from agriculture, forestry, and other land use: A spatial panel econometric analysis

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Abstract

This paper provides a quantitative assessment of the effects of input and output prices on French GHG emissions from agriculture, forestry and other land use (AFOLU) at the NUTS2 level. Reduced-form, random-effect spatial error models are estimated for four emissions categories (nitrogen use, manure management, enteric fermentation, and land use, land-use change and forestry) in order to account for both spatial autocorrelation and spatial unobserved heterogeneity. The main findings are: (i) price impacts on emission levels are found to be significant, although sign and magnitude vary from one emission category to the other, (ii) estimated price effects are more apparent when emission categories are analyzed separately rather than aggregated, and (iii) the spatial dimension is found to play an important role. The estimated models are then used to simulate the effects of a doubling of crop prices on AFOLU emissions. The results indicate that this would lead to an 11%-increase in agricultural sources.

Key words: AFOLU, greenhouse gas emissions, spatial autocorrelation, panel data

JEL classification: Q15, Q54, C31, C33

1. Introduction

Land-based sectors are significant contributors to the accumulation of greenhouse gas (GHG). Farming activities are responsible for a large share of global anthropogenic methane (CH_4) and nitrous oxide (N_2O) emissions, while Land Use, Land-Use Changes, and Forestry (LULUCF) constitutes a major source of CO_2 emissions globally. Moreover, LULUCF may also contribute to sequester carbon in soils and/or above-ground biomass. Recently, these sources and sinks have come under increasing scrutiny because of their potential role in the global cost-effective mitigation mix. In France, agricultural sources account for approximately 20% of total emissions, whereas LULUCF represent a net sink that offsets about 10% of total emissions (CITEPA, 2010). Altogether, sources and sinks from Agriculture, Forestry, and Other Land Uses (AFOLU) may thus play a pivotal role in meeting French ambitious mitigation targets. From 1990 to 2005, the decrease in these emissions has contributed to the decline of French GHG emissions more than any other sector. Since 2005, however, this contribution has however considerably lessened. This raises the question of the influence of the significant price increases that have characterized the recent period. This question is of great policy importance for determining the mitigation effort that might be expected from AFOLU. The overall aim of this paper is to provide some quantitative insight into this issue.

The links between land-based sectors and GHG emissions have been examined in previous literature along two main lines of research. First, sectoral models of agriculture and/or forestry have been utilized to investigate the impacts of policy instruments on GHG emissions (for a survey, see Vermont and De Cara, 2010). In these models, the relationships between prices and emissions are generally implicit. Second, econometric models have been used to estimate the determinants of land-use, from which some GHG sources and sinks can then be calculated (e.g. Lubowski et al., 2006; Plantinga et al., 1999). The scope is however usually restricted to LULUCF emissions and spatial effects are largely overlooked.

Recent developments in spatial econometrics provide new methods for accounting for spatial effects in land-use models, in particular through the use of random effect spatial error models (Chakir and Le Gallo, 2013). We build on these developments to estimate reduced-form models of the main GHG sources/sinks category from AFOLU as functions of input and output prices. We consider random effect spatial error models (RE-SEM) that capture both time-invariant heterogeneity across *Departements* (NUTS2) and spatial effects that may arise from omitted variables that have a spatial structure. The contribution of this paper is twofold. First, we provide a quantitative assessment of the effects of input and output prices on GHG emissions from AFOLU. Second, we estimate econometric models that capture both individual heterogeneity and spatial autocorrelation. To the best of our knowledge, spatial autocorrelation and unobserved heterogeneity have been ignored in previous studies addressing this issue.

The paper is structured as follows. We present the econometric model in section 2 and the data in section 3. In section 4, estimation results are discussed. We use these results to simulate the impact on emissions of a doubling of crop prices in section 5. Section 6 concludes.

2. The model

AFOLU sources/sinks result from a number of different land-based activities. Some are related to livestock, others to crop or to land management. The underlying economic decisions are often made by different agents and subject to different time horizons. Nevertheless, they are related to each other through land allocation (cropland vs. grassland vs forestland vs other uses) and input use (e.g. fertilizer use, animal feeding, substitution between synthetic fertilizer and manure spreading). The complexity of these interactions emissions make it very challenging, if not impossible, to derive a tractable structural model capable of (i) representing the relevant decisions regarding crop allocation, livestock production, input use, and land use within a unified framework, and (ii) estimating explicitly the relationships between prices and emissions. To our best knowledge, there is no structural econometric model in the literature addressing simultaneously crop, livestock, and land-use at a sufficient level of details to provide relevant insight into the implications for GHG emissions.

In this paper, we circumvent this difficulty by considering a reduced-form modeling strategy.[1] We consider the French GHG sources/sinks from AFOLU at the *Departement* level (96 departments in Mainland France). The model allows to control for both individual heterogeneity and spatial correlation across *Departements*. Ignoring spatial correlation and heterogeneity due to the random *Departement* effects may result in inefficient estimates and misleading inference (Chakir and Le Gallo, 2013). Let y_{mit} denote the GHG emissions in category m, *Departement* i, and time t and assume that y_{mit} is generated according to the following model:

$$y_{mit} = x_{mit}\beta_m + u_{mit}, \tag{1}$$

$$u_{mit} = \mu_{mi} + \varepsilon_{mit}, \tag{2}$$

$$\varepsilon_{mit} = \lambda_m \sum_{j=1}^{N} w_{ij}\varepsilon_{mjt} + v_{mit}, \tag{3}$$

[1]As discussed in Timmins and Schlenker (2009), "*both structural and reduced form models have their own context-specific advantages and disadvantages, and should be viewed as complements, not substitutes*".

where x_{mit} is a $k \times 1$ vector of observed individual specific regressors on the ith cross-section unit at time t ($i = 1, \ldots, N$ and $t = 1, \ldots, T$), w_{ij} is the generic element of a nonnegative, $N \times N$ spatial-weight matrix W, μ_{mi} is the random *Departement* effect assumed to be $IID(0, \sigma^2_{\mu_m})$, ε_{mit} is the spatially autocorrelated error term, λ_m is the spatial autocorrelation coefficient, and v_{mit} is an IID error term with zero mean and variance σ^2_v.

We control in our model for unobserved individual heterogeneity. From an econometric point of view, individual effects can either be assumed as random variables or fixed parameters. The choice between the random-effect (RE) or fixed-effect (FE) specification depends on the model and data (Baltagi, 1995; Lee and Yu, 2010b). In a spatial setting, using individual fixed effects might induce an incidental parameter problem as the asymptotics in the cross-sectional dimension is necessary. Some papers (Lee and Yu, 2010a) have provided methods in order to overcome this problem. However, in a fixed-effect model, time-invariant spatial clusters will be "swept away" by the within estimator and the associated coefficient cannot be identified. For this reason we choose to model individual effects through random effects. This choice imposes that the individual effects are independent of exogenous regressors. In the empirical section this hypothesis will be tested using Hausman test statistics.

In our model, spatial autocorrelation can arise from two possible sources (LeSage and Pace, 2009). First, it may arise from unobservable latent variables that are spatially correlated. Omitted variables that are spatially correlated can result in an estimation bias as soon as they are also correlated with one or more of the observed spatial variables. In our case, this may be due to underlying pedo-climatic characteristics (e.g., dairy production tends to take place in rainy areas, cereal production is located on plains, etc.) that are correlated over space. Moreover, the geographic distribution of agricultural systems partly results from historical and institutional determinants (e.g., the location of intensive livestock production is partly linked to infrastructure such as harbor facilities for importing soybeans, the production of vegetables tends to be close to consumption centers, etc.). Second, it may arise because of the measurement error spillovers across neighboring boundaries or because of the scale mismatch and the inherent need to integrate data from different scales. For example, data on fertilizers delivery at the *Departement* level do not always reflect where these fertilizers are used. This is particularly true when deliveries are made to harbors or distribution organizations, which then distribute fertilizers to other *Departements*. The spatial weight matrix used in this paper is the Gabriel Neighbors matrix (Matula and Sokal, 1980).[2] The matrix W is constant over time. To estimate panel data models that include spatially correlated error terms, we use the maximum likelihood approach Anselin (1988); Baltagi et al. (2003); Elhorst (2003).

In matrix form, Eq. (1) becomes (index m is omitted):

$$y = X\beta + u \tag{4}$$

y and u are of dimension $NT \times 1$, X is $NT \times K$, β is $K \times 1$. The observations are sorted first by time t and then by spatial units i. Equation (2) can be rewritten in vector form as:

$$u = (i_T \otimes I_N) + [I_T \otimes B^{-1}]v \tag{5}$$

with $B = I_N - \lambda W$, i_T is a vector of ones of dimension T, I_T is an identity matrix of dimension T and $\otimes$ denotes the Kronecker product. The log-likelihood function of the spatial random effects

[2] Any two points are considered to be Gabriel neighbors if the enclosing circle formed with the distance between these two points as diameter contains no other point. An alternative (Delauney) weight matrix has also been tested. The estimation results were found to be robust.

model is (Anselin, 1988):

$$L = -\frac{NT}{2} ln 2\pi\sigma_v^2 - \frac{1}{2} ln[|T\phi I_N + (B'B)^{-1}|] + \frac{T-1}{2} ln|B'B| - \frac{1}{2\sigma_v^2} e'\Sigma_u^{-1} u \tag{6}$$

with $u = y - X\beta$, $\phi = \frac{\sigma_\mu^2}{\sigma_v^2}$ and

$$\Sigma_u^{-1} = \bar{J}_T \otimes \left(T\phi I_N + (B'B)^{-1}\right)^{-1} + E_T \otimes (B'B) \tag{7}$$

with $\bar{J}_T = J_T/T$, $E_T = I_T - \bar{J}_T$, J_T is a matrix of ones of dimension T.

β and σ_v^2 can be computed from the first-order maximizing conditions. In the absence of analytical solution, the parameters ϕ and λ given β and σ_v^2 are obtained numerically by using the two-stage iterative procedure proposed by Elhorst (2003). In a first stage, whereby $\widehat{\beta}$ and $\widehat{\sigma_v^2}$ are computed by setting initial values for ϕ and λ. In the second stage, ϕ and λ are estimated by maximizing the concentrated log-likelihood.

3. Data

The computation of emissions closely follows the methodology used in French GHG inventories CITEPA (2010). Emissions are calculated by multiplying activity variables by emission factors that are specific to each emission category. Emissions are calculated at the *Departement* level,Non-CO_2 emissions are converted into tCO_2eq using Global Warming Potentials (25 for CH_4, 298 for N_2O). Emissions are normalized by the total area of the respective *Departement*.

Emissions from the use of synthetic fertilizers (EMNITR) are computed by multiplying nitrogen quantities at the *Departement* level (1990-2007, taken from UNIFA (2009)) by the emission factors used in CITEPA (2010). These factors account for the shares of applied nitrogen that are leached and volatilised and are constant over time and space.

CH_4 emissions from enteric fermentation (EMFERM) are calculated by using animal numbers (taken from AGRESTE, 2011b) and animal-specific emission factors. The emission factor associated with dairy cattle depends on milk yield. This emission factor thus varies over time and space according to the average milk yield at the *Departement* level (taken from AGRESTE, 2011b). The emission factor associated with non-dairy cattle varies according to the herd composition. The emission factors associated with the remaining animal categories are constant over time and space.

Emissions from manure (EMMANU) include emissions occurring during manure storage (N_2O and CH_4) and N_2O (direct and indirect) emissions due to manure spreading on agricultural soils. N_2O emissions related to manure storage depends on the amount of nitrogen produced by animals and the manure management system. Nitrogen quantities are calculated by multiplying livestock numbers and per-head nitrogen coefficients for each animal category (CITEPA, 2010). The share of nitrogen managed under each system is based on the average national distribution of solid and liquid management systems. The emission factors related to CH_4 emissions from manure management and storage are specific to each animal category. The computation of N_2O emissions due to nitrogen excretion by animals on pastures and manure spreading on agricultural soils is similar to that of EMNITR.

Net emissions from LULUCF (EMLUCF) are calculated by multiplying the acreage changing from one land use to another between year $t-1$ and t. Each pair of land uses (i,k) is associated with a region-specific emission factor that corresponds either to a source (+) or sink (-) of CO_2 due to the conversion of one hectare from i in year $t-1$ to k in year t. Land-use data are taken from TERUTI (AGRESTE, 2004), in which 550,903 points throughout mainland

France are surveyed on a yearly basis over the 1993-2003 period[3]. Each point is associated with land-use category (among 81 categories). These data were used to calculate yearly land use changes for each observed point and each pair (i,k) among the nine following categories: coniferous forest, decidious forest, poplar, mixed forest, cropland, pastures, urban, wetlands, and other uses. Region-specific emission factors that account for carbon stock changes in both biomass and soils have been obtained from CITEPA. These factors vary over time and space.

Crop, cattle, milk, hog, and fertilizer prices at the country level over the 1990-2007 period are taken from Eurostat (2011). Wood prices were obtained from the *Laboratoire d'Economie Forestière (LEF)*. Grassland prices were taken from AGRESTE (2011a). When need be, prices are deflated using a Harmonized Index of Consumer Prices from OECD (2011). In order to limit multicollinearity, crop prices (wheat, barley, rapeseed, maize, sunflower) were grouped into one index using crop areas at the *Departement* level from AGRESTE (2011b) as weights:

$$pcrop_{it} = \frac{\sum_{c=1}^{5} p_{ct} S_{cit}}{\sum_{c=1}^{5} S_{cit}} \tag{8}$$

where c is the index for crop, p_{ct} is the price of crop c in year t and S_{cit} is the area of crop c in *Departement* i in year t. A similar approach was used to compute the cattle price index ($pcatt_{it}$) from cattle and milk prices using dairy and non-dairy animal numbers as weights:

$$pcatt_{it} = \frac{p_t^{non-dairy} N_{it}^{non-dairy} + p_t^{milk} N_{it}^{dairy}}{N_{it}^{non-dairy} + N_{it}^{dairy}} \tag{9}$$

where $N_{it}^{non-dairy}$ and N_{it}^{dairy} are non-dairy and dairy cattle numbers, in *Departement* i in year t. $p^{non-dairy}$ and p^{milk} are non-dairy cattle and milk price in year t, respectively. Therefore, $pcrop_{it}$ and $pcatt_{it}$ vary over both space and time. All prices are converted into indexes (year 2000 = 100). Summary statistics are reported in table 1.

Table 1. Explanatory variables: Summary statistics, sources, and description

	variable	Source	Mean	Std.dev.	Spatial resolution
crop price index	$pcrop_{it}$	(1)	116.23	24.20	Departement
cattle prices	$p_t^{non-dairy}$	Eurostat	109.46	21.90	country
milk prices	p_t^{milk}	Eurostat	98.01	7.95	country
cattle price index	$pcatt_{it}$	(1)	106.86	18.05	Departement
hogs prices	$phogs_t$	Eurostat	102.63	17.77	country
wood prices	$pwood_{it}$	LEF	101.85	19.24	Departement
N fertilizer prices	$pfert_t$	Eurostat	104.54	11.11	country
grassland prices	$pgras_{it}$	Agreste	103.29	25.15	Departement

(1): own calculations (See text).

A previous study showed strong evidence of global and local spatial autocorrelation for each emission category (Chakir et al., 2011). Results from that study are used to construct spatial clusters of *Departements*. The corresponding variable cl_{mi} has five modalities: "Hh", "Ll", "Lh", "Hl", and "no", which depends on whether there is significant spatial auto-correlation and, if so, whether emissions of category m in *Départment* i are high (H) or low (L) and i is surrounded by high- (h) or low-emissions (l) *Départments*. These clusters were computed based on cumulative emissions over the sample period. They are therefore constant over time.

[3]TERUTI data are not available to us before 1993 and for the years between 2004 and 2006.

4. Estimation results

Four estimators are considered: (i) pooled OLS, which ignores individual heterogeneity and spatial correlation, (ii) random-effect (RE) estimator, which accounts for random individual heterogeneity but ignores spatial correlation, (iii) spatial error model (SEM) estimator, which accounts for autoregressive spatial error autocorrelation but ignores individual heterogeneity, and (iv) the RE-SEM estimator, which accounts for both spatial error autocorrelation and random individual heterogeneity.

Equations for EMNITR, EMMANU, EMFERM, and EMAGRI (sum of agricultural sources) are estimated over the 1990-2007 period using a logarithm transformation of the dependent variables and of the price variables. The estimated coefficients thus have a straightforward interpretation as a price elasticity. Given the lack of data for EMLUCF and EMNET (total net emissions) after 2003, equations for these two emissions are estimated over the 1993-2003 period. In addition, as these emission categories may have negative values, they were estimated without any log transformation of the variables.

The Hausman (1978) test based on the difference between FE and RE estimators is used to analyze the consistency of the RE estimator. We use the joint and the conditional LM tests developed by Baltagi et al. (2003) for error correlation as well as random individual effects (see Table 2). The χ^2_k statistics (k is the number of regressors that are not constant over time) for the Hausman test are not statistically significant at 1% for each emission category. The null hypothesis is not rejected confirming that the RE estimator is consistent for each emission category. The joint test for spatial error correlation and random effects (T1) as well as the conditional tests for spatial error correlation (T2) and random individual effects (T3) are significant at 1% for each emission category (except (T3) for EMLUCF). This justifies the choice of a model taking into account both spatial error autocorrelation and random individual heterogeneity (RE-SEM).

Table 2. Specification tests

Tests	Hypothesis	EMNITR	EMMANU	EMFERM	EMAGRI	EMLUCF	EMNET
HT	H_0: RE is more efficient	$\chi^2_4 = 0.50$	$\chi^2_3 = 0.02$	$\chi^2_3 = 0.00$	$\chi^2_4 = 0.00$	$\chi^2_5 = 0.22$	$\chi^2_7 = 0.57$
	H_1: RE is inconsistent	(0.97)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
T1	H_0: $\sigma^2_\mu = \lambda = 0$	11551.83	13414.47	13475.52	13135.13	2974.10	3943.52
	H_1: $\sigma^2_\mu \neq 0$ or $\lambda \neq 0$	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
T2	H_0: $\lambda = 0$ (ass $\sigma^2_\mu \geq 0$)	15.64	16.62	16.02	15.37	2.15	7.23
	H_1: $\lambda \neq 0$ (ass $\sigma^2_\mu \geq 0$)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
T3	H_0: $\sigma^2_\mu = 0$ (allowing $\lambda \neq 0$)	4.81	2.70	4.67	4.11	0.82	4.94
	H_1: $\sigma^2_\mu > 0$ (allowing $\lambda \neq 0$)	(0.00)	(0.00)	(0.00)	(0.00)	(0.21)	(0.00)

For tests T1 to T3, the values reported are the lagrange multiplier statistics of the tests, p-values are between brackets.

Estimation results are reported in tables 5 to 6 (in appendix). Because of the lack of a satisfying counterpart of the R^2 (Elhorst, 2009), we evaluate the goodness-of-fit by using the squared correlation coefficient between actual and fitted values ($corr^2$). The values of $corr^2$ suggest that the RE-SEM model fits reasonably well our data. For all emission categories, results from both the RE and the RE-SEM models confirm the existence of random individual heterogeneity (ϕ significant at the 1% level). Moreover, the spatial autocorrelation parameter λ is also significant (at the 1% level) for both the SEM and the RE-SEM models. This confirms the results of the specifications tests in favor of the RE-SEM estimator.

Table 3 summarizes the estimation results in terms of elasticities. For each individual emission category, crop prices have a positive and significant effect on the corresponding emissions (significance level of at least 5%). Higher crop prices tend to increase per-hectare emissions for

Table 3. Summary of price elasticities from the RE-SEM model by emission category

	EMNITR	EMMANU	EMFERM	EMAGRI	EMLUCF	EMNET
$pwood_{it}$					0.111	0.115
$pcrop_{i,t-1}$	0.532***	0.047**	0.068***	0.151***	0.340*	0.616
$pfert_{it}$	-0.160*			-0.081***		0.619
$pcatt_{i,t-1}$	-0.224**	0.061***	0.003	-0.027	0.411**	0.879**
$phogs_{i,t-1}$		0.086***	0.039*			0.490
$pgras_{it}$	-0.044			0.058***	0.000	-0.002

Significance levels: ***: 0.01, **: 0.05, *: 0.1.

The elasticities for EMLUCF and EMNET are calculated as the mean change in predicted emissions due to a 1% increase of each respective price over the mean predicted emissions holding all variables constant.

each category. Among agricultural emission sources, crop prices have the greatest impact on emissions due to synthetic fertilizer use (elasticity of 0.53). Estimated elasticities for manure management and enteric fermentation are around ten times lower. The responsiveness of EMNITR to crop prices may explained by both intensive and extensive margin effects: *(i)* higher crop prices encourage larger N application rates, and *(ii)* increased crop profitability favors conversions to cropland. The latter effect may also explain the positive effect of crop prices on emissions from LULUCF. The resulting effect of crop prices on EMAGRI and EMNET is positive, although not significant for EMNET. Fertilizer prices have a negative and significant effect on EMNITR and EMAGRI. The elasticity of fertilizer prices on EMNITR is however more than three times lower than that of crop prices on the same emission category. We find no significant impact of wood and grassland prices on the emissions due to LULUCF.

The sign of the coefficients associated with cattle prices differ between emission categories. As expected, higher cattle prices tend to increase emissions from manure and enteric fermentation. The effect of cattle prices on EMFERM is however not significant for the RE-SEM model. On the contrary, higher cattle prices tend to lower emissions from the use of synthetic fertilizers. This negative effect may result from (i) the conversion of croplands into pastures (the increase in the profitability of animal production increasing the need for pastures) and (ii) the substitution of synthetic fertilizers for organic fertilizers. The results suggest that the latter effect dominates. Lastly, the positive effect of cattle prices on total net emissions suggests that the combined effects of cattle prices on each individual emission source is positive. Hog prices have a positive and significant effect on EMMANU and EMFERM.

The dummy for the year 2000 has a significant effect on emissions from LULUCF (at 5%) and total net emissions (at 1%). This captures the large amount of carbon released in the aftermath of the 1999 storms. For each emission category, the *HH* and *LL* modalities of the cluster variables have a significant effect on emissions. *Departements* for which $cl_{mi} = HH$ ($cl_{mi} = LL$) tend to have significantly (at 1%) higher (lower) values of emissions than the others.

5. Predictions

The best linear unbiased predictor (BLUP) when both error components and spatial autocorrelation are present is (Baltagi and Li, 1999):

$$\widehat{y}_{iT+S}^{RE-SEM} = x_{iT+S}\widehat{\beta}^{RE-SEM} + T\phi \sum_{j=1}^{N} \delta_j \bar{u}_{j.}, \tag{10}$$

Table 4. Root Mean Square Error for the four predictors

	OLS	SEM	RE	RE-SEM
EMNITR	0.35	0.35	0.35	0.17
EMMANU	0.42	0.44	0.41	0.05
EMFERM	0.32	0.34	0.32	0.04
EMAGRI	0.74	0.75	0.74	0.19
EMUTCF	0.93	0.95	0.94	0.67
EMNET	1.38	1.44	1.40	0.78

where $\phi = \frac{\sigma_\mu^2}{\sigma_v^2}$, δ_j is the jth element of the ith row of V^{-1} with $V = T\phi I_N + (B'B)^{-1}$ and $\overline{u}_{j.} = \sum_{t=1}^{T} \widehat{u}_{jt}/T$, with $\widehat{u}_{it} = y_{it} - x_{it}\widehat{\beta}$. For the RE model (Baltagi and Li, 2006), the spatial autocorrelation correction is null and the BLUP reduces to:

$$\widehat{y}_{iT+S}^{RE} = x_{iT+S}\widehat{\beta}^{RE} + \frac{T\sigma_\mu^2}{T\sigma_\mu^2 + \sigma_v^2}\overline{u}_{j.} \tag{11}$$

For the OLS and the SEM estimators the BLUP correction term is null.

For each model, the BLUP is calculated using the sample estimation periods. Predictions are then compared with observed data available for 2008 for agricultural sources and 2007 for EMLUCF and EMNET. Root Mean Square of Errors (RMSE) are reported in table 4. For each emission category, the RMSE is of the same magnitude for the first three estimators but it markedly drops for the RE-SEM estimator. This suggests that the RE-SEM estimator provides more accurate predictions. Its performance is however much greater for agricultural emission sources than for emissions from LULUCF and total net emissions.

The RE-SEM predictor is then used to simulate the effects of a doubling of crop prices. All explanatory variables, excluding crop prices, are taken at their observed values for the last sample year. The predicted values of the changes in emissions are depicted in Figure 1. It shows that a 100% increase in crop prices (holding all other variables constant) leads to an increase of about 45% of EMNITR, 3% of EMMANU and 5% of EMFERM at the national level. This illustrates the higher price-responsiveness of emissions from the use of synthetic fertilizer relative to animal-related emissions. Changes in emissions are not evenly distributed over space. The effects of a crop price increase seem to be higher in Departements for which observed 2007 emission were higher. The total agricultural emissions increase is about 10.5 MtCO2eq which corresponds to a 11% increase compared to predicted emissions taking all variables at their 2007 observed values. Using the abatement supply curve given by De Cara and Jayet (2011, table 2), compensating such an increase would require a tax of approximately 33 €.tCO_2eq^{-1}, which is significantly higher than the current carbon price on the European Emission Trading market. These results also indicate a much greater impact on EMLUCF (and consequently on EMNET) than on agricultural sources. This should however be interpreted with caution as the prediction accuracy for emissions from LULUCF is much lower than for agricultural emissions.

6. Conclusion

The objective of this paper was to assess the effects of input and output prices on GHG sources/sinks from AFOLU at the *Departement* level in France. To this end, various estimation methods have been applied to reduced-form models of the relationship between emissions and

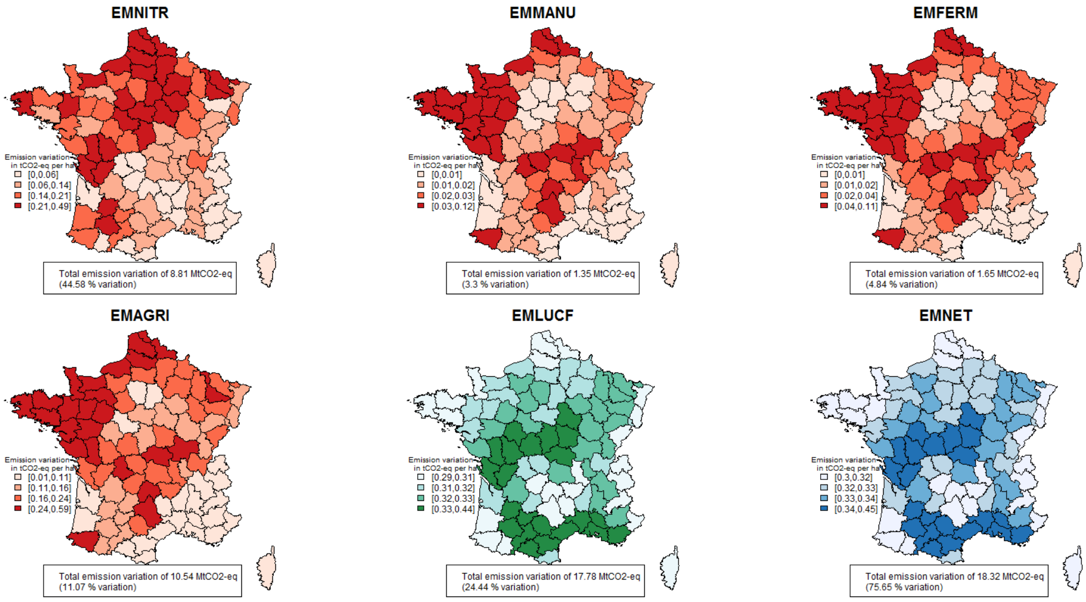

Figure 1. Emission variation for a 100% variation of crop price index

prices. Results of the specification tests show that the random effect spatial error models (RE-SEM) estimator suits the best our data and leads to more accurate predictions than alternative estimators (OLS, random error, and spatial error models). These results confirm the importance of taking into account both spatial error autocorrelation and random regional effects.

Our main empirical findings are threefold. First, prices do have an impact on both the level and spatial distribution of emissions. This result highlights the importance of taking into account the spatial structure of the various emissions categories. Second, the price effects are more significant for individual emission categories than for total net emissions from AFOLU. Separating emission sources and sinks thus allows us to differentiate price effects that are masked at the aggregated level. Third, the price effects are more important for N_2O emissions due to synthetic fertilizer use than for other agricultural sources. Our results suggest that prices have an important impact on both the level and the structure of the mitigation potential by emissions categories. This effect should thus be taken into account in the design of public policies aimed at reducing emissions or enhancing carbon sinks in these sectors.

The use of a reduced form has the advantage to summarize the complex interactions that exist between the various emission categories, whilst keeping the approach relatively simple. However, it does not allow us to explicitly describe the chain of events linking economic land-use decisions to AFOLU emissions. Further research is needed along these lines.

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Appendix

Table 5. Estimation results for emissions from agriculture ($N = 89$, $T = 18$)).

	Dependant variable: $\ln(EMFERM)$				Dependant variable: $\ln(EMMANU)$			
	OLS	RE	SEM	RE-SEM	OLS	RE	SEM	RE-SEM
Intercept	-1.36**	-1.32***	-1.49	-1.25***	-1.74***	-1.51***	-1.80***	-1.5***
	(0.565)	(0.095)	(1.080)	(0.097)	(0.533)	(0.092)	(0.445)	(0.099)
$\ln(pcrop_{i,t-1})$	0.037	0.069***	-0.015	0.068***	-0.068	0.064***	-0.098	0.047**
	(0.223)	(0.016)	(0.269)	(0.024)	(0.210)	(0.018)	(0.220)	(0.023)
$\ln(pcatt_{i,t-1})$	0.047	0.024*	0.094	0.003	0.185	0.059***	0.216	0.061***
	(0.188)	(0.014)	(0.231)	(0.020)	(0.178)	(0.015)	(0.193)	(0.019)
$\ln(phogs_{i,t-1})$	0.050	0.032**	0.072	0.039*	0.129	0.073***	0.140	0.086***
	(0.183)	(0.013)	(0.239)	(0.020)	(0.173)	(0.015)	(0.185)	(0.019)
$cl_{mi} = LL$	-1.60***	-1.60***	-1.27***	-1.60***	-1.42***	-1.42***	-1.31***	-1.42***
	(0.047)	(0.196)	(0.059)	(0.165)	(0.044)	(0.185)	(0.041)	(0.185)
$cl_{mi} = HH$	1.12***	1.12***	1.15***	1.12***	1.37***	1.37***	1.33***	1.37***
	(0.053)	(0.223)	(0.062)	(0.188)	(0.054)	(0.229)	(0.059)	(0.229)
λ			0.226***	0.438***			0.113***	0.272***
			(0.021)	(0.028)			(0.018)	(0.031)
ϕ		191***		160***		139***		149***
		(29.4)		(18.3)		(21.5)		(23)
R^2	0.55	0.22	0.58		0.56	0.31	0.56	
$corr^2$				0.55				0.56
$logLik$		2179.25	-1070.10	2287.79		2035.89	-1011.50	2072.42

	Dependant variable: $\ln(EMNITR)$				Dependant variable: $\ln(EMAGRI)$			
	OLS	RE	SEM	RE-SEM	OLS	RE	SEM	RE-SEM
Intercept	-3.68**	-1.56***	-4.07***	-1.63***	-0.24	-0.14	-0.34	-0.12
	(1.430)	(0.407)	(0.84)	(0.565)	(0.922)	(0.143)	(1.130)	(0.173)
$\ln(pcrop_{i,t-1})$	0.760***	0.437***	0.942***	0.532***	0.162	0.148***	0.169**	0.151***
	(0.198)	(0.053)	(0.229)	(0.075)	(0.127)	(0.017)	(0.083)	(0.022)
$\ln(pfert_{i,t})$	-0.277	-0.180***	-0.226	-0.160*	-0.090	-0.083***	-0.065	-0.081***
	(0.234)	(0.063)	(0.144)	(0.091)	(0.151)	(0.020)	(0.185)	(0.026)
$\ln(pcatt_{i,t-1})$	-0.516**	-0.146**	-0.671***	-0.224**	-0.039	-0.019	-0.020	-0.027
	(0.233)	(0.063)	(0.254)	(0.089)	(0.150)	(0.020)	(0.114)	(0.026)
$\ln(pgras_{i,t})$	0.577***	-0.021	0.571***	-0.044	0.095	0.062***	0.055	0.058***
	(0.198)	(0.058)	(0.199)	(0.059)	(0.127)	(0.019)	(0.126)	(0.019)
$cl_{mi} = LL$	-1.48***	-1.48***	-1.25***	-1.48***	-1.20***	-1.20***	-0.88***	-1.20***
	(0.054)	(0.221)	(0.063)	(0.221)	(0.040)	(0.168)	(0.031)	(0.168)
$cl_{mi} = HH$	0.71***	0.71***	0.61***	0.71***	1.09***	1.09***	1.06***	1.09***
	(0.064)	(0.261)	(0.069)	(0.262)	(0.046)	(0.193)	(0.054)	(0.193)
$cl_{mi} = LH$	-0.02	-0.03	-0.10	-0.03				
	(0.152)	(0.624)	(0.148)	(0.623)				
$cl_{mi} = HL$	0.22	0.20	0.41**	0.20				
	(0.213)	(0.873)	(0.207)	(0.873)				
λ			0.19***	0.361***			0.236***	0.256***
			(0.0145)	(0.0311)			(0.0192)	(0.0319)
ϕ		13***		14.6***		55***		58.2***
		(2.02)		(2.26)		(8.5)		(8.99)
R^2	0.42	0.14	0.45		0.52	0.2	0.56	
$corr^2$				0.42				0.52
$logLik$		-222.45	-1506.75	-162.09		1533.45	-774.03	1563.59

Significance levels: ***: 0.01, **: 0.05, *: 0.1. Standard deviations in parentheses.

Table 6. Estimations results for net emissions from land use, land use change and forestry and aggregated net AFOLU emissions ($N = 89$, $T = 11$).

	Dependant variable: $EMLUCF$				Dependant variable: $EMNET$			
	OLS	RE	SEM	RE-SEM	OLS	RE	SEM	RE-SEM
Intercept	-2.6***	-2.69***	-2.3***	-2.29***	-1.51*	-1.79***	-0.965	-1.46***
	(0.264)	(0.172)	(0.322)	(0.24)	(0.774)	(0.296)	(0.944)	(0.555)
$pwood_t$	5.69e-05	0.00243*	0.00027	0.00126	-0.0046	0.0022	-0.00248	0.000743
	(0.00177)	(0.00131)	(0.00181)	(0.00109)	(0.00282)	(0.00139)	(0.00281)	(0.00112)
$pcrop_{i,t-1}$	0.00763***	0.00673***	0.00475*	0.00345*	0.0162***	0.00934***	0.0165***	0.00356
	(0.00246)	(0.00117)	(0.00286)	(0.00191)	(0.00536)	(0.00169)	(0.00632)	(0.00231)
$pfert_{i,t}$					0.00508	0.00477***	0.00605	0.00411
					(0.00529)	(0.00164)	(0.00658)	(0.00386)
$pcatt_{i,t-1}$	0.00363*	0.0033***	0.00411*	0.00439**	0.000645	0.00311**	-0.00166	0.00534**
	(0.00209)	(0.000983)	(0.00243)	(0.00187)	(0.00396)	(0.00124)	(0.00475)	(0.00211)
$phogs_{i,t-1}$					-0.00304	-0.000106	-0.00793	0.00307
					(0.00426)	(0.00133)	(0.00484)	(0.00261)
$pgras_{i,t}$	0.000264	0.00018	0.000204	4.61e-06	0.00196	0.000305	0.00176	-1.15e-05
	(0.000837)	(0.000413)	(0.000822)	(0.000298)	(0.00132)	(0.000432)	(0.00127)	(0.000305)
$yr2000$	0.275***	0.265***	-0.114	0.225**	0.314**	0.315***	-0.249	0.317***
	(0.0917)	(0.0428)	(0.115)	(0.0971)	(0.157)	(0.0486)	(0.193)	(0.115)
$cl_{mi} = LL$	-1.14***	-1.16***	-1.04***	-1.14***	-1.94***	-2.01***	-1.85***	-1.98***
	(0.0678)	(0.195)	(0.0743)	(0.199)	(0.109)	(0.332)	(0.125)	(0.336)
$cl_{mi} = HH$	1.57***	1.57***	1.46***	1.56***	3.87***	3.89***	3.47***	3.88***
	(0.0646)	(0.19)	(0.0728)	(0.195)	(0.111)	(0.35)	(0.135)	(0.354)
$cl_{mi} = LH$	-0.297	-0.319	-0.411*	-0.324				
	(0.239)	(0.705)	(0.235)	(0.704)				
λ			0.171***	0.666***			0.22***	0.681***
			(0.0168)	(0.0285)			(0.0189)	(0.0276)
ϕ		3.56***		5.97***		9.46***		16.3***
		(0.575)		(0.965)		(1.5)		(2.61)
R^2	0.56	0.24	0.57		0.67	0.3	0.69	
$corr^2$				0.56				0.67
$logLik$		-567.31	-798.86	-397.77		-652.14	-1231.57	-469.43

Significance levels: ***: 0.01, **: 0.05, *: 0.1. Standard deviations in parentheses.