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Assessing the Impact of Agri-Environmental Management Practices on Farm Productivity When Adoption is Endogenous

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Abstract

Environmental management practices for mitigating nutrient runoff affect the productivity of agricultural land. Finland's agricultural policy offers a number of such practices, and we use Finnish grain farms as a case study of these productivity impacts. Productivity is endogenous with adoption when decision-makers can choose from a menu of policy options, but few studies actually address this endogeneity. Our identification strategy thus involves a novel approach for correcting endogeneity, combining classic methods from stochastic frontier analysis and selection models. Using registry data from 2007-2013, we find that the more efficient farms are also more likely to enroll in management practices. Standard estimates without the endogeneity correction understate productivity losses after adoption.

Keywords: Agri-Environmental Programs; Non-Point Pollution; Productivity; Stochastic Frontier Analysis; Endogeneity; Selection model; Sparse Grid

JEL Classification: C14, Q12, Q52,

1 Introduction

The United States and European Union have taken different paths in developing agri-environmental programs (AEPs). The US has implemented a very limited number, most notably land retirement under the Conservation Reserve and the Wetlands Reserve, and management practices under the Environmental Quality Initiatives. The EU has enacted a much wider array through the Common Agricultural Policy (CAP). This regulation establishes environmental and rural-development goals for EU agriculture as a whole, but gives member states flexibility in designing incentives. The EU has historically emphasized management practices for working land, while the US has enacted these practices only recently (Baylis et al. 2008).

Working-land AEPs often require substantial changes to existing agricultural processes, with potentially large impacts on productivity. As these policies expand, it becomes increasingly important to quantify their productivity implications. However, the literature on EU AEPs focuses nearly exclusively on environmental impacts (Ohl et al. 2008, Wätzold et al. 2008, Pufahl and Weiss 2009, Chabé-Ferret and Subervie 2013, Laukkanen and Nauges 2014), leaving the first-order relationship between AEP participation and agricultural productivity largely unexplored.[1]

In this paper, we investigate the productivity impacts of AEPs in Finnish agriculture. With one of the highest AEP participation rates in the EU, Finland serves as an ideal case study of these effects. More than 90% of Finnish agricultural land is enrolled in some kind of AEP, compared to 25% across the fifteen older EU members (European Commission 2005). Finland also enrolls the most land – about 95% in Finland versus 26% across the EU – in AEPs that require input reductions. These practices, such as the curtailment of chemical applications, have an tremendous impact on agricultural productivity. Finland has also enacted a number of supplemental measures, such as further reductions in fertilizer, cover crops and conservation tillage, and riparian zones. Unlike the basic measures, there is considerable variation in the adoption of supplemental measures. We use this differential in uptake to identify the impact of specific AEP practices on productivity.

Endogeneity is an important concern when estimating these productivity effects, because a farm's perception of the efficiencies across the menu of available AEP practices is likely to influence its adoption decision. If uncorrected, this latent selection effect leads to biased efficiency estimates. While this problem has been widely acknowledged in the productivity literature, very few studies perform an endogeneity correction. In fact, we know of just one other: Kumbhakar et al. (2009) examine a farm's decision to adopt organic practices using an endogenous stochastic frontier analysis (SFA). The authors jointly estimate the binary decision to go organic or not, and the productivity resulting from that decision.

Our identification strategy enhances this vital correction in two ways. First, by using a multinomial framework, we can model more than two options in the first-stage AEP-selection decision. Second, we allow for arbitrary correlation among the unobservable inefficiency terms. Both of these extensions reflect decision features that managers of Finnish farms face when choosing from the AEP policy menu. But, accommodating them precludes a closed-form solution of the likelihood function, and so we also develop a feasible sparse-grid method for evaluating the likelihood numerically. To our knowledge, ours is the first study to account for endogeneity of more than two decision options within an SFA-style framework, while simultaneously allowing for arbitrary inefficiency correlations.

Because this model is highly nonlinear, we begin our analysis with a brief simulation study of the sampling distributions, for some intuition about asymptotics. The results on a toy example indicate that the Central Limit Theorem can be reasonably assumed to apply in samples of 10^3 to 10^4 observations. Unfortunately, even when perfectly specified, a model estimated on 10^2 observations tends to have flat sampling distributions, particularly in the first-stage endogeneity correction. We thus suggest caution when applying this method, because the data requirements are likely to be substantial. However, our sample size falls in the ideal range, making us more confident about the asymptotics of our study.

We estimate the model on a repeated cross-section of Finnish grain farms from 2007-2013, constructed from registry data. Because we use standard (though restricted) data sources, the method we outline can be used for AEP assessments in other EU member states. Our results also have important policy implications for the increased reliance on environmentally-benign management practices in the US.

[1] Some policy analysis of French agriculture has been conducted in this vein (Piot-Lepetit and Moing 2007, Mary 2013).

2 Background

The efficiency implications of AEPs are a timely topic of research (Zhao et al. 2004, Feng et al. 2006, Rabotyagov et al. 2010). Finnish policy in this area is primarily shaped by concerns about runoff into the Baltic Sea hypoxic zone. However, studies of the productivity impacts of water-pollution AEPs are relatively rare. Tamini et al. (2012) conduct one of them, examining the use of manure injection and herbicide reduction in Canadian crop farms using a Bayesian-Malmquist model (Atkinson and Dorfman 2005). Because they have data on both farm and environmental outcomes, the authors can estimate the "environmental efficiency" of a farm's uptake, in addition to its productivity and profitability. They find that adopting herbicide reduction decreases technical efficiency, but that the freed labor and capital help to increase productivity. Manure injection slightly increases technical efficiency and productivity, and substantially increases profitability. Apropos to our study, they also find a positive relationship between technical efficiency and environmental efficiency.

Finnish grain farms have provided a particularly fruitful case study for policy research on AEPs. Laukkanen and Nauges (2011) estimate a structural model of no-till practices on production costs and nutrient/herbicide loading. Laukkanen and Nauges (2014) exploit regional differences in basic AEP payments when estimating input use, and simulate the resulting effects on nutrient loading. They find that the implementation of basic water-protection measures, such as vegetative filter strips and winter cover crops, leads to 11-13% reductions in nutrient loadings.

The productivity of Finnish farms has been examined in a few other contexts. As mentioned previously, Kumbhakar et al. find that a farm's inefficiency reduces its likelihood of adopting organic practices, even though a subsidy is available. Moreover, those farms going organic are ultimately about 5% less efficient than those that do not. Nauges et al. (2011) develop a state-contingent model that captures uncertainty and inefficiency in the production decisions. They find that the substitution of land use among alternative grain crops in different states of nature largely conforms to theoretical predictions.

Finland enacted its AEP program upon joining the EU in 1995. Its policy applies nationwide, unlike those of most other members. However, the program's scope has increased since the introductory years, and so we focus exclusively on Finland's third AEP period from 2007-2014. This relatively mature regulation entails two levels of participation: "basic measures" and "additional and/or special measures." Basic measures for nutrient loading impose fertilizer limits by crop and region, and require 3 m filter strips for crops adjacent to waterways. Basic-measure subsidies for arable crop farms are 93 EUR/ha, and participation exceeds 90%. The non-binding character of the fertilizer limits may explain this steep uptake rate (Laukkanen and Nauges 2014).

Farms may also participate in "additional measures" and "special measures." (The latter require concurrent enrollment in basic measures.) For crop farms, these AEPs include further reductions in fertilizer use, more accurate application of fertilizer, reduced tillage, winter cover crops, long-term crop rotation, nutrient balance, riparian zones, and organic production. Subsidies in this part of the regulation vary by measure and crop, and participation rates range from about 10-30%.[2] This variation in participation rates, coupled with farm-level detail on the uptake of practices, allows us to evaluate the productivity impacts of AEPs, much like Tamini et al. do.

The literature on AEP implementations elsewhere in the EU is also growing. Topics include the farm's participation decision (Hynes et al. 2008, Giovanopoulou et al. 2011), the spatial distribution of measures (Wätzold and Drechsler 2005, Bamière et al. 2011), and general efficacy (Ohl et al. 2008, Wätzold et al. 2008, Pufahl and Weiss 2009, Chabé-Ferret and Subervie 2013). Contributing to this stream of research, we estimate the productivity impacts of three of Finland's most widespread practices. Conjointly, we provide a new way of addressing endogeneity between production efficiency and AEP adoption, while still retaining the intuition of an SFA framework.

[2] The Rural Development Programme for Mainland Finland 2007-2013 provides extensive detail on eligibility, subsidy amounts, and participation rates.

3 Simultaneous Policy Selection and Output Choice

We describe a farm's decision in two stages. Each of I farms first chooses from a menu of J AEP practices, and then produces output under the selected practice. Starting with the production step and working backward, farm i's output under practice j is given by the standard log-log production model

$$y_{ij} = x_i'\beta_j + \varepsilon_{ij}$$

where y_{ij} is (log) output, x_{ij} is a (log) vector of observable input factors, and ε_{ij} are unobservable input factors. The unobservables are further decomposed into explicit inefficiencies u_{ij} (positive by definition) and all other production characteristics v_{ij}, so that $\varepsilon_{ij} = -u_{ij} + v_{ij}$. This decomposition of the error structure mirrors classic SFA (Aigner et al. 1977).

The classic framework, however, requires random assignment of farms to practices, and this does not occur in reality. Instead, a farm chooses optimally from the menu of practices in the AEP regulation, based on the manager's assessment of how profitable each is likely to be. Farm i's selection of practice j is thus underpinned by the expected-profit model

$$\pi_{ij} = z_i'\gamma_j + \delta u_{ij} + \eta_{ij}$$

where z_i is a vector of observed profitability factors, and η_{ij} are unobserved profitability factors. From our perspective as econometricians, we observe the AEP choice j and the resulting output y_{ij}, but not the set of J intermediate expected-profit calculations π_{ij}. These are latent judgments, but play a major role in driving the two observed outcomes. Except for the presence of the unobservable inefficiency term u_{ij} in the profit equation, this setting is much like the classic two-stage selection model (Heckman 1979).

Our fundamental econometric issue lies in the presence of the inefficiency in both decision stages. Intuitively, an endogeneity problem arises because the productivity implications of practice j will affect the farm's decision of whether to adopt it. Mathematically, this means that the inefficiency term u_{ij} enters both the initial selection from the AEP policy menu and the ultimate output. Treating adoptions as randomly assigned – thus ignoring the selection step – would tend to overstate the farm's production efficiency.

To frame the issue in likelihood terms, suppose we observe farm i implementing AEP practice $m_i = j$ and producing $y_i = y_{ij}$. Denote the vector of J inefficiencies that farm i incurs under the menu of AEP policies as u_i. From our perspective as econometricians, the likelihood $f(y_i, m_i)$ of this occurring is

$$\begin{aligned} f(y_i, m_i = j) &= E_{u_i}\left[f(y_i, m_i = j|u_i)\right] \\ &= E_{u_i}\left[f(y_i|m_i = j, u_i)\, f(m_i = j|u_i)\right] \\ &= E_{u_i}\left[f(v_{ij}|m_i = j, u_i)\, f(m_i = j|u_i)\right] \\ &= \int_{\mathbb{R}^{J+}} f(v_{ij}|m_i = j, u_i)\, f(m_i = j|u_i)\, dF(u_i) \end{aligned}$$

If we jointly estimate the model parameters $\beta_1, \ldots, \beta_J$, $\gamma_1, \ldots, \gamma_J$, and δ using this likelihood function, the endogeneity will be successfully corrected.

However, this likelihood involves a potentially complex multivariate integration, and so the empirical literature often makes simplifying assumptions to maintain its tractability. One common simplification is that m_i and v_{ij} are independent, that is, that the selection effect is random with respect to the non-inefficiency unobservables. This assumption would essentially collapse the model back to classic SFA. It entails a slightly more technical statement about the selection bias – addressing just the v_{ij} aspects in the residual ε_{ij} – but its underlying intuition is the same. Almost assuredly, the unobserved factors driving output for farm i under practice j are similar to those driving the initial decision to adopt practice j. This decision feature forecloses any radical simplification of the selection stage by assuming the independence of m_i.

Another routine simplification is that the inefficiencies are all independent, an assumption that conveniently reduces $dF(u_i)$ to a product of likelihoods. However, the AEP practices we investigate all share

common operational features, suggesting that the elements of u_i are instead quite correlated. Indeed, one of the practices we examine is a combination of two others, guaranteeing correlation within u_i almost by definition.

We can evaluate this likelihood while retaining the requisite correlations by placing additional structure on the unobservables. For the output equation, we adopt a common SFA-style normal/half-normal structure for ε_{ij}. The conditional density of the production unobservables v_{ij} is normal

$$v_{ij}|m_i = j, u \sim N\left(0, \sigma_{vj}^2\right)$$

and the unconditional density of inefficiencies u_i is half-normal

$$u_i \sim N^+\left(0, \Sigma_u\right)$$

Importantly, unlike standard SFA, the distribution of u_i has an unrestricted covariance matrix Σ_u.

In the selection equation, we use a standard Gumbel distribution for the unobserved profitability factors η_{ij}:

$$\eta_{ij}|u_i \sim GEV\left(0, \sigma_\eta^2, 1\right)$$

This yields a logit probability for the adoption of practice j:

$$f\left(m_i = j|u_i\right) = \frac{\exp\left(z_i'\gamma_j + \delta u_{ij}\right)}{1 + \sum_{j'=1}^{J-1} \exp\left(z_i'\gamma_{j'} + \delta u_{ij'}\right)}$$

For identification purposes, we normalize the γ_j parameters in the logit relative to the Jth practice, and set the shape parameter σ_η^2 to 1.

With this error specification, the likelihood now has the slightly more tractable form

$$f\left(y_i, m_i = j\right) = \int_{\mathbb{R}^{J+}} \left[\frac{1}{\sigma_{vj}}\phi\left(\frac{y_i - x_i'\beta_j + u_{ij}}{\sigma_{vj}}\right)\right]\left[\frac{\exp\left(z_i'\gamma_j + \delta u_{ij}\right)}{1 + \sum_{j'=1}^{J-1} \exp\left(z_i'\gamma_{j'} + \delta u_{ij'}\right)}\right] dF\left(u_i\right)$$

However, this is substantially more involved than the regular, closed-form SFA likelihood that arises without selection bias or inefficiency correlation:

$$f\left(y_i, m_i = j\right) = \frac{1}{\sigma_{vj}}\phi\left(\frac{y_i - x_i'\beta_j + u_{ij}}{\sigma_{vj}}\right) \cdot \frac{1}{\sigma_{uj}} \frac{\phi\left(u_{ij}/\sigma_{uj}\right)}{\Phi\left(u_{ij}/\sigma_{uj}\right)}$$

Comparing the two shows that our main tractability issue stems from the arbitrary covariance structure we allow within u_i. The integral has has potentially high dimension, leaving a limited number of options for evaluating it numerically. We discuss two of them.

The first is an integration-by-simulation strategy based on the Geweke-Hajivassiliou-Keane simulator (Keane 1994). This involves sampling from an easier, related distribution $g\left(u_i\right)$ – the multivariate normal, in this case – and mapping those samples to $f\left(u_i\right)$. Letting $M\left(u_i\right)$ denote the integrand of the likelihood, the key relationship in the simulator is the identity

$$\int_{\mathbb{R}^{J+}} M\left(u_i\right) dF\left(u_i\right) = \int_{\mathbb{R}^J} M\left(u_i\right) \frac{f\left(u_i\right)}{g\left(u_i\right)} g\left(u_i\right) du_i$$

Using the "importance weight" $w\left(u_i\right) = \frac{f(u_i)}{g(u_i)}$, the integral can be approximated with S simulations from $g\left(u_i\right)$:

$$\int_{\mathbb{R}^{J+}} M\left(u_i\right) dF\left(u_i\right) \simeq \frac{\frac{1}{S}\sum_{s=1}^{S} M\left(u_i^s\right) w\left(u_i^s\right)}{\frac{1}{S}\sum_{s=1}^{S} w\left(u_i^s\right)}$$

The numerator in this last expression approximates the likelihood for an non-truncated, joint-normal distribution, while the denominator approximates the truncation probability.

Though easy to implement, the GHK technique exhibits unacceptable levels of approximation error in our setting. In the toy example we present in the next section for asymptotic intuition, we find that obtaining two digits of integration accuracy requires $S \approx 10^4$ points. Because integration-by-simulation relies on convergence in probability, improvements in accuracy come only at a $\sqrt{S}$ rate (at best). This

implies that an exponentially-larger number of simulations would be needed to achieve every additional digit of accuracy. This finding does not bode well for the tractability of our actual model with $I = 10^3$ to 10^4 observations, each of which requires an integration at every iteration of a maximum-likelihood algorithm. We thus do not even report results based on the GHK simulator, because the approximation error is likely far too high.

Instead, we perform the integration using a sparse grid, a set of multidimensional quadrature points ω_i^s and associated scalar weights q_i^s. While integration-by-simulation relies on a side effect of the Law of Large Numbers (i.e., convergence in probability), sparse grids are constructed specifically to minimize integration error (Gerstner and Griebel 1998). As a result, a smaller number of points S is needed to achieve the same level of precision. The form of the approximation is similar to a weighted average:

$$\int_{\mathbb{R}^{J+}} M(u_i)\, dF(u_i) \simeq \frac{1}{S} \sum_{s=1}^{S} M(\omega_i^s)\, f(\omega_i^s)\, q_i^s$$

In our toy example, we obtain 3 to 4 digits of accuracy using a sparse grid with $S \approx 10^2$ points, a far more tractable strategy.

Sparse grids are defined over simple regions of the real domain, and so the quadrature points must be explicitly mapped to more complicated regions of interest like ours. We employ the Gauss-Legendre grid, which defines integration over the $[-1,1]^J$ hypercube. We must map these points to $\mathbb{R}^{J+}$ while simultaneously imputing the correct correlation structure. Our strategy makes each point ω_i^s in the original grid analogous to a "draw from a uniform distribution" $\bar{\omega}_i^s$, to which the "inverse distribution function" $F^{-1}(\bar{\omega}_i^s)$ is applied, resulting in a draw u_i^s from the target distribution. This procedure involves two steps:

1. The original grid point ω_i^s is linearly translated to a point $\bar{\omega}_i^s$ in the uniform-distribution domain $[0,1]^J$.
2. The uniform point $\bar{\omega}_i^s$ is translated to $F(u_i^s)$. Because this distribution has arbitrary correlation as well as truncation, the vector must be composed sequentially, with each element of u_i^s accounting for the correlation structure that was previously imposed within it.
   (a) For the jth element in the vector, an intermediate draw scalar draw $\bar{u}_{ij}^s$ is taken from a standard univariate truncated-normal distribution, using the uniform scalar $\bar{\omega}_{ij}^s$ from step 1. To capture the existing correlation from elements before the jth, the lower truncation bound is set to the z-score $\frac{0-\sum_{j'=1}^{j-1} \bar{u}_{ij'}^s \sigma_{ujj'}}{\sigma_{ujj}}$, where $\sigma_{ujj'}$ denotes the (j,j') element of the correlation matrix $\Sigma_u^{1/2}$.[3]
   (b) After step (a) has been applied to all J elements in the vector, the correlated, truncated standard draw $\bar{u}_i^s$ is translated into a draw from $N^+(0, \Sigma_u)$ through the affine transformation $u_i^s = 0 + \sum_u^{1/2} \bar{u}_i^s$.

Importantly, one must remember to apply the change-of-variable formula for integration with each modification to the grid point. This ensures that the integrand $f(\omega_i)\, d\omega_i$ integrated over $[-1,1]^J$ corresponds to $f(u_i)\, du_i$ integrated over $\mathbb{R}^{J+}$.

4 Finite-Sample Properties

When this model is correctly specified and the sampling process is random, the Central Limit Theorem guarantees that the maximum-likelihood estimator is consistent and asymptotically normal. The essential requirement is $I \to \infty$, but it is not at all clear what this entails in a highly nonlinear model like the one outlined above. Before delving into the main policy analysis, we conduct a brief simulation study of the model's finite-sample properties using a toy example with $J = 2$ options, and $I = 100$ or $I = 1000$ observations. Samples on this order are typical in empirical work.

[3] If the elements of u_i are uncorrelated (i.e., if the inefficiencies do not share common features), this process yields a series of uncorrelated standard half-normal draws, corresponding to a multivariate SFA model.

The example uses a single-input production model and a single-criterion profit model, so that both x and z are 2×1 vectors (including a constant term in each). The values of each vector are drawn orthogonally, making the exercise nonparametrically identified by construction. The error variances are set so that about half of the variation in each equation comes from the observables, and half from the unobservables. Moreover, the elements of u_i are made uncorrelated. In our view, this scenario would be a very favorable one to encounter in a real empirical setting.

Table 1 lists the first three moments of the simulated sampling distributions for samples of size $I = 100$ and $I = 1000$. In each case, we simulated one thousand datasets. A few aspects of the finite-sample behavior are important. First, the estimators of β in the production equation appear to be centered fairly well at the correct value, as the Central Limit Theorem would predict. However, their spread is quite large for $I = 100$, a finding corroborated by their histograms in Figure 1. These estimators are thus marginally trustworthy when $I = 100$, but fairly robust when $I = 1000$.

Second, the estimators of γ and δ in the selection equation behave quite poorly when $I = 100$. The center of γ is off by a factor of four, and the standard deviation is multiple times the center. These are all indications that the Central Limit Theorem does not yet apply. (We actually truncate the histograms for $I = 100$ in Figure 2 to the range of the $I = 1000$ histograms, because a meaningful amount of the $I = 100$ density lies more than five standard deviations away from the mean.) Overall, convergence is much slower in the selection equation: the center moves in the correct direction when $I = 1000$, but the standard deviation is still large. The sampling distribution of δ, which is almost entirely flat when $I = 100$ (indicating that the inefficiency impact is completely unidentified), starts to become more defined by $I = 1000$. Even so, it is still about 20% too low, and retains a very high spread. The estimators of γ are thus reasonably robust when $I = 1000$, but the estimator of δ is still not very reliable.

Third, the estimators of σ_v appear to be trustworthy at first glance when $I = 100$. However, their nearly-correct central values belie a double peak in their sampling distributions, evident only from the histograms in Figure 3. Of course, the Central Limit Theorem permits no such bimodality, and these estimators are actually quite poor by implication. However, they are once again reliable by $I = 1000$.

Finally, the estimators of Σ_u converge extremely slowly. The issue is that they frequently uncover some spurious correlation among the inefficiencies when the sample is small. The histogram of the covariance in Figure 4 reveals a correct modal estimate near 0, accompanied by a long left tail. The skew in this estimator persists even at $I = 1000$, a feature at odds with the symmetric distribution predicted by the Central Limit Theorem. Thus, this estimator is questionable even when $I = 1000$.

To summarize, β, γ, and σ_v are reasonably well-identified when $I = 1000$, but δ and Σ_u are not. The latter finding is unfortunate, because we are specifically interested in the endogeneity of u_i in the selection and output stages, which is exactly the interplay between Σ_u and δ. These latter parameters converge slowly even though this toy example is nearly ideal by construction: it has no specification error with only single-predictor equations, guaranteed nonparametric identification, and about half of the outcome variation explained by observables.

The practicalities of the Central Limit Theorem are therefore of paramount concern when applying this endogeneity correction. The technique is very much a large-sample one: even if the model is perfectly specified, the estimates are probably unreliable in samples of just hundreds. Fortunately, the imprecision manifests itself rather obviously through large standard errors, making it easy for the econometrician to assess ex post whether small-sample bias is a likely concern. Our sample contains almost $I = 5000$ observations and appears to generate precise estimates, giving us more confidence about the asymptotic behavior here.

5 Data

Our data comes from the restricted government database "Statistics on the Finances of Agricultural and Forestry Enterprises," maintained by Statistics Finland. It includes incomes, expenses, assets, and liabilities at the farm level. The repeated cross-section we construct is a combination of tax-registry data and a detailed input/output survey. The former is a full panel of all active Finnish farms, while the latter is a rolling cross-section of them that are interviewed for two consecutive years.

To ensure that we a model a coherent technological space, we focus exclusively on the active farms cultivating grain. "Active farms" in Finland are defined as crop farms with at least one ha under cultivation, and animal farms with at least one ha under cultivation or at least one animal being raised. Our sample thus includes crop farms explicitly defined as such, and those animal farms also cultivating grain.

Production variables are generally recorded in revenue and expenditure form. We back out the underlying quantities using price index values taken from the "Yearbook of Farm Statistics" and the "Producer Prices of Agricultural Products."

AEP participation variables come from a second restricted database "Farm Accounting and Income Statistics" (MYTT) maintained by Finland's Agency for Rural Affairs. This registry identifies the farms receiving AEP payments, including the land area enrolled in each measure, and the amounts paid.

The Finnish AEP system is jointly financed by the EU and Finland. The first program period (1995-1999) furnished flat region- and crop-specific basic payments for a few environmental practices. Finland's AEP system was subsequently revised in conjunction with the EU's Agenda 2000 CAP reform. The second AEP period (2000-2006) introduced flexibility through "additional measures," and decoupled AEP payments from their prior linkage to crop and region. In 2003, the Fischler reform fundamentally changed the EU CAP, resulting in a third policy period (2007-2014). This rather substantial set of amendments increased Finland's budget for AEPs, and again altered the menu of eligible measures.

Table 2 lists the "additional measures" that were enacted during Finland's second and third AEP periods. While some policy overlap exists, several entirely new measures were introduced in the third period, and some of the second-period ones were refined. While the Finnish registry data do cover part of the second period, the large number of regulatory changes leads us to treat the third period as a complete policy break. By limiting ourselves to just this period, we can estimate efficiency relationships without developing an ancillary control strategy for the differences in program implementation.

Figure 5 decomposes AEP expenditures by basic, additional, and special measures from 2004-2014. Basic payments are always above EUR 200M, and a persistent jump in additional and special payments occurs at the start of the third period. Figures 6 and 7 present the average annual land area enrolled in each measure during the the second and third periods. The upsurge in payments is reflected in the land areas as well, with large enrollments in accurate nitrogen application (policy 2) and winter cover crops / reduced tillage (policy 3). Of course, farms were not limited to only one measure; Figures 8 and 9 show the average annual land area enrolled in each measure combination. While policies 2 and 3 are often used exclusively, they are also frequently used in conjunction with another practice.

Given the extensive adoption of policies 2 and 3 relative to the others, we focus on the farm's choice from a menu consisting of policy 2 alone, policy 3 alone, and the combined 2 & 3 policy. This restriction leaves us with a enough cohort of farms in each policy group to identify the applicable implementation tradeoffs. We compare them to a base group that did not enroll in any additional measures. (One third of these farms did not even enroll in the basic program.) We thus model $J = 4$ options, indexing them in order of popularity: $j = 1$ for policy 3, $j = 2$ for policy 2, $j = 3$ for policy 2 & 3, and $j = 4$ for non-adopters.

Table 3 summarizes our data. In the production equation, we include the standard agricultural inputs land, fertilizer, machinery, and fuel. We omit labor, because most Finnish farms do not employ workers outside the family. The SEU variables are geographic indicators used by the EU central government to define subsidy zones, with higher SEU numbers conveniently indicating more northerly regions.[4] To control for climate and weather differences across regions and years, we include average temperature, precipitation, and growing season length.

In the selection equation, we include potential instruments for selection bias. First, we include attributes of the farm and its management. We proxy work experience with the farm manager's age. We also include an indicator of whether a farm is near the Baltic Sea, because the Finnish government more heavily recruits these farms to control their runoff. We proxy a farm's financial health with its debt-to-asset ratio, and the subsidy payments it receives under the EU-wide CAP and Least Favored Area (LFA)

[4] We exclude SEUs 5, 6, and 7 from the productivity analysis. Located in the far north (partly above the Arctic Circle), these farms face substantially different growing conditions from the rest of Finland. Fortunately, they comprise less than 1% of the sample.

programs. We conjecture that more indebted farms may perceive AEP payments to be more lucrative, and that farms receiving AEP-like payments from the EU central government may be more likely to enroll in the Finnish national measures.

We also include average participation rates at the municipality level in the selection equation. Municipalities constitute a smaller geographic area than SEUs, and so these averages capture a shared local rationale for adopting or rejecting the AEPs. As a result, they correlate reasonably well with farm-level adoption decisions. Moreover, municipal-level uptake rates probably do not enter an individual farm's output decision. Hence, they are likely to be strong and exogenous instruments.

Farms adopting policy 3 tend to be larger, use more inputs, and receive higher CAP and LFA payments. They are also more likely to be found in the more southerly SEUs 1 and 2. The size and input use of farms adopting policy 2 generally fall between the policy 3 group and the non-adopting group. These farms are more concentrated in the more northerly SEUs 3 and 4. Like those adopting policy 3, adopters of the combined policy tend to be larger farms, but they are more evenly distributed across SEUs. Finally, the non-adopting group is found primarily in SEUs 2-4, and is concentrated most highly in SEU 3. Farms opting out receive lower EU subsidies (likely due to their smaller size) and are less indebted. They are also more likely to be found in municipalities with higher rates of non-adoption.

6 Results

We begin with reduced-form estimates of each decision stage, as a point of reference for evaluating endogeneity bias. For reduced-form production, we estimate standard log-log and SFA models by AEP policy group. For reduced-form selection, we estimate a multinomial logit.

In the log-log estimates in Table 4, each of the production inputs has the expected sign (except machinery, on occasion). Somewhat surprisingly, temperature and growing season negatively affect output in all but the base group. This outcome could be attributable to nonlinearities in the marginal effect of weather (Schlenker and Roberts 2008). Relative to the base region SEU 1, crop yields are higher in SEU 2 and lower in SEUs 3 and 4. Relative to the base year 2007, yields are generally lower over the rest of the third AEP period, particularly for those farms enrolling in policy 2 and the combined policy.

The SFA estimates largely mirror those of the log-log model, except that the weather coefficients are cut nearly in half. The SFA model thus appears to attribute many of the negative effects of weather in the log-log model to outright inefficiency. The highly-precise estimates of σ_{uj} imply mean inefficiencies of 0.768, 0.679, 0.760, and 0.679 (in log t) to the four practices.

The logit model contains all variables from the production equation for statistical efficiency, as well as the selection instruments. Because we are most interested in the ability of the instruments to generate exogenous selection variation for the joint model's first stage, we focus on their estimates in Table 5. Farm and farm management characteristics are largely insignificant in the adoption decision, with the exception of the debt/asset ratio for policy 3 adopters, and the LFA subsidy for policy 2 adopters. The municipal average uptake rates, on the other hand, are quite significant in all groups, and have the expected signs. For instance, farms situated in municipalities with higher uptake of policy 2 are less likely to adopt policy 3, as are those located in areas with higher opt-out rates. Similarly, farms in municipalities with higher uptake of policy 2 are themselves more likely to adopt policy 2. Finally, farms situated in areas that uptake each policy separately are more likely to choose the combined policy.

The instruments are not jointly significant in any of the production models, and so they are to be likely exogenous to production. Moreover, the pseudo-R^2 of the logit model is 0.35 with these instruments and 0.24 without, with most of that increase coming from the municipal uptake rates. Thus, the first stage is likely to contribute a moderate amount of exogenous selection variation in the joint model.

Table 6 presents the joint estimates of each production equation. Land and fertilizer effects are on par with those in estimated in reduced form. Weather effects remain negative. The region and time indicators are also similar in sign and magnitude to those of the SFA model.

The biggest difference in moving to the the joint estimates comes from the efficiency assessment. For all four practices, the joint estimates reveal much less efficient production in all but the non-adopters: the σ_u estimates here imply average inefficiencies of 1.576, 2.082, 1.818, and 0.460 (in log t). Although the

production estimates are less precise overall in the joint model (reflecting a typical bias-variance tradeoff), the estimates of the error variances remain quite precise.

Table 7 presents the instruments in the jointly-estimated selection equation. Like their reduced form analogs, we find a positive effect of indebtedness in adopting policy 3. In addition, we now find a positive effect for LFA subsidies in all three policy options, and a positive effect for CAP subsidies in policy 2 and the combined policy. Importantly, we again find highly significant effects for the municipal uptake rates in all three groups.

These joint selection estimates reveal another important driver of adoption: the vector of inefficiencies u_i. The strongly negative estimate of δ indicates that inefficient farms are much more likely to opt out. This fact helps to explain the higher mean inefficiencies we estimated under SFA, because that specification assumes no selection bias. The efficiency losses from implementing each AEP measure are thus larger now, because the more productive farms are actually the ones opting in. This result echoes the finding by Kumbhakar et al. that efficient farms are more likely to select into organic practices, but that once doing so, they become less efficient than their non-organic peers.

Finally, we present estimates of $\Sigma_u^{1/2}$ in Table 8. The covariance terms are all quite large, and most of them are precise. As we conjectured, strong commonalities exist among the inefficiencies of these practices. For example, the inefficiency of the combined policy is negatively correlated with the inefficiency of policy 3, and positively correlated with the inefficiency of policy 2. This indicates that efficiency tradeoffs are present when farms implement both policies at once. Moreover, the inefficiency associated with opting out is negatively correlated with the inefficiencies of all other practices. In other words, as these practices all become more efficient, the efficiency loss from choosing none of them rises.

7 Policy Implications

We have examined the productivity impacts of three leading AEPs in Finland for reducing nutrient runoff: (1) winter cover crops coupled with reduced tillage, (2) applying fertilizer more accurately, and (3) using both practices together. We compare these relative to a base group of non-adopters. In designing the impact study, we developed a novel extension of classic SFA that (a) corrects for the endogeneity between a farm's inefficiency and its decision to adopt an AEP practice, and (b) allows for correlation among unobserved inefficiency characteristics across the menu of practices.

In estimating the joint production/selection effects on Finnish grain farms, we find that the more inefficient ones are more likely to opt out of these practices. Compared to standard SFA, ignoring this selection effect appears to substantially understate the inefficiency. We also find that farms that do adopt practices generally become more inefficient, compared to those that opt out.

This result has important policy implications for the design of AEP incentives. Because the more productive farms are the ones more likely to enroll, the efficiency losses resulting from AEP adoption may entail higher production costs than previously thought. This would support policy arguments for additional compensation to cover the actual losses, and for better training farm managers on implementing these practices. Our results may also explain the disparity between Finland's near-universal participation in basic AEP measures, and its substantially lower uptake rates in additional and special measures.

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Appendix: Figures and Tables

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Figure 1: Simulated sampling distributions of β (production equation).

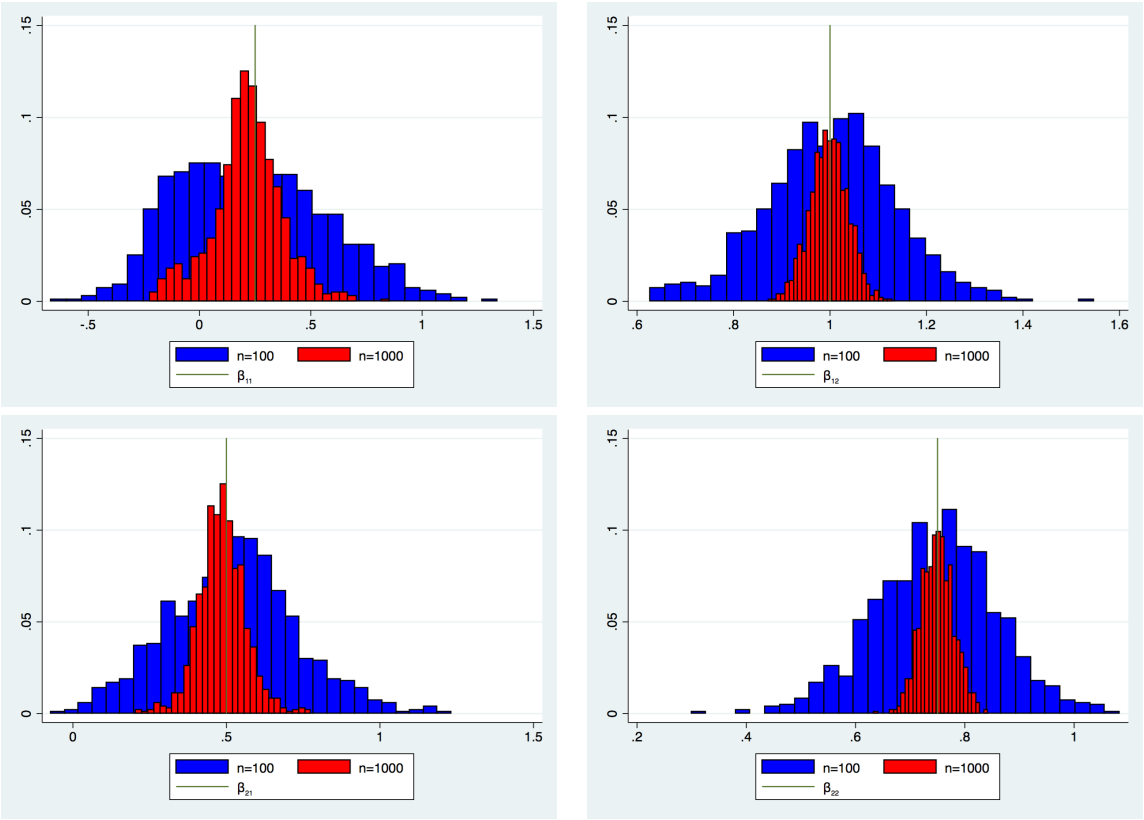

Figure 2: Simulated sampling distributions of γ and δ (selection equation).

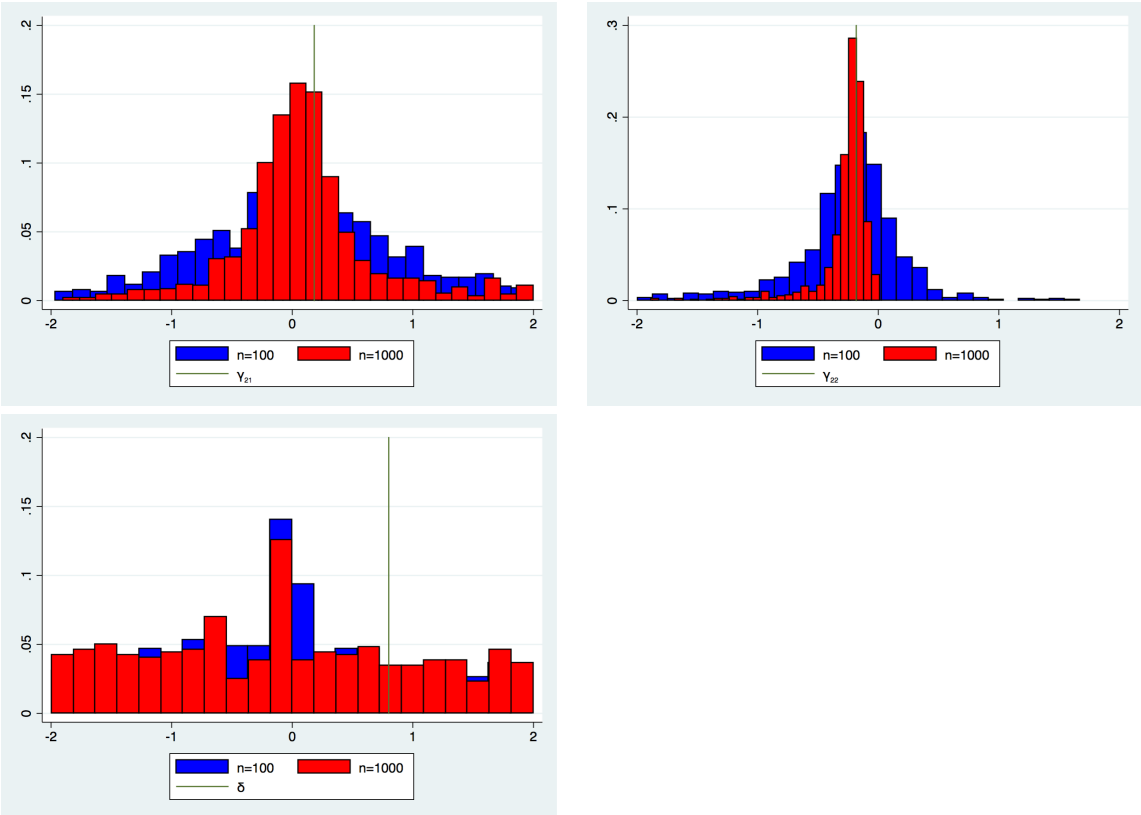

Figure 3: Simulated sampling distributions of σ_v (unobserved production characteristics).

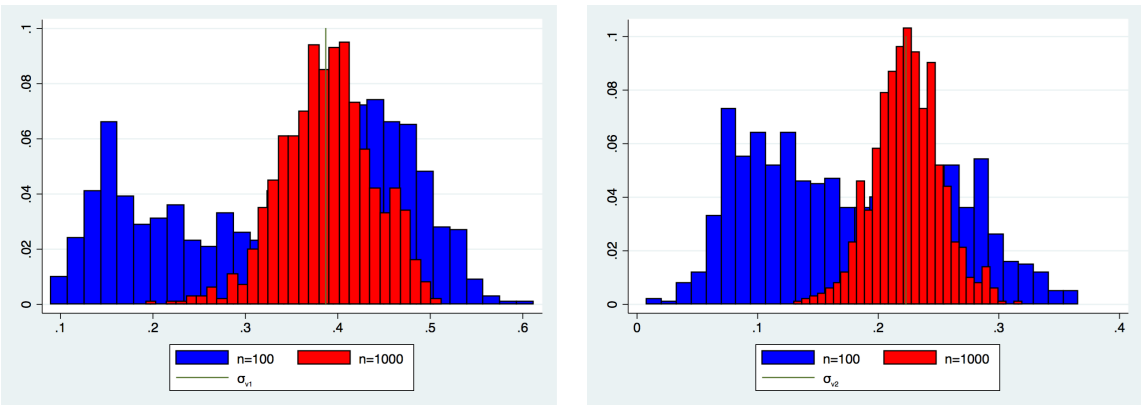

Figure 4: Simulated sampling distributions of σ_u (unobserved inefficiencies).

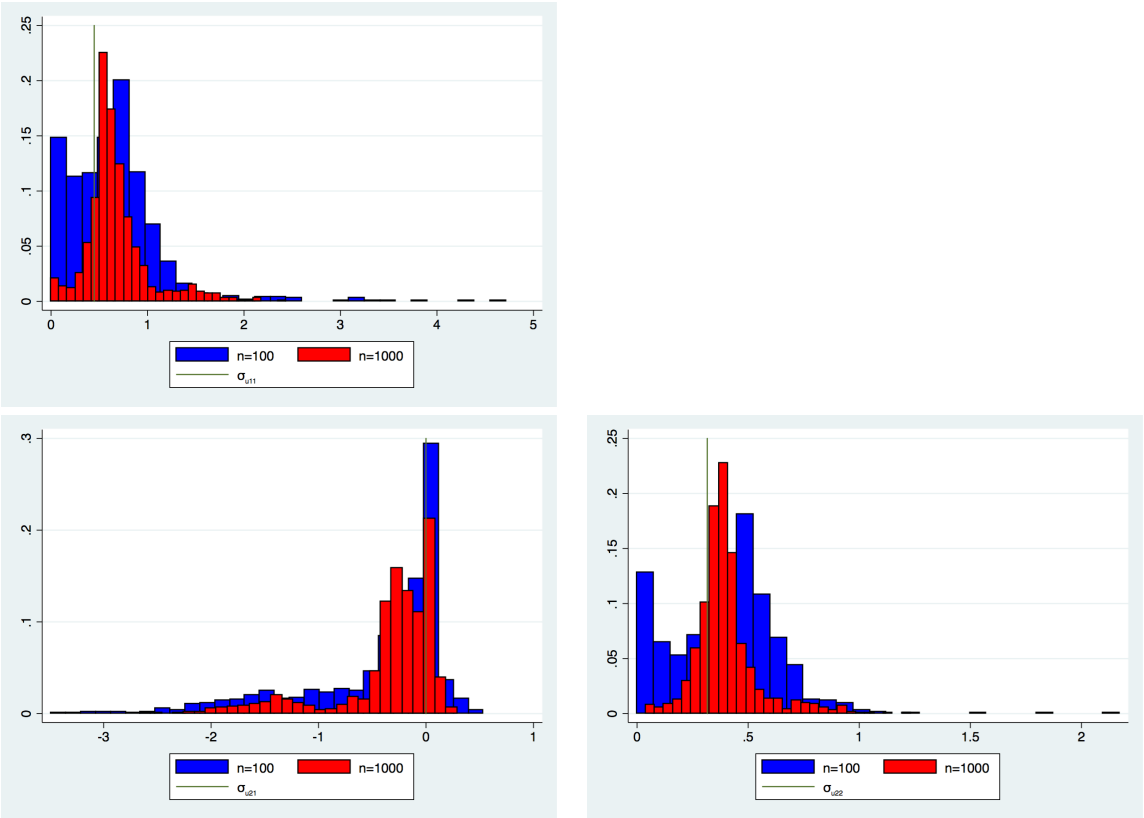

Figure 5: Total AEP spending, 2004-2014.

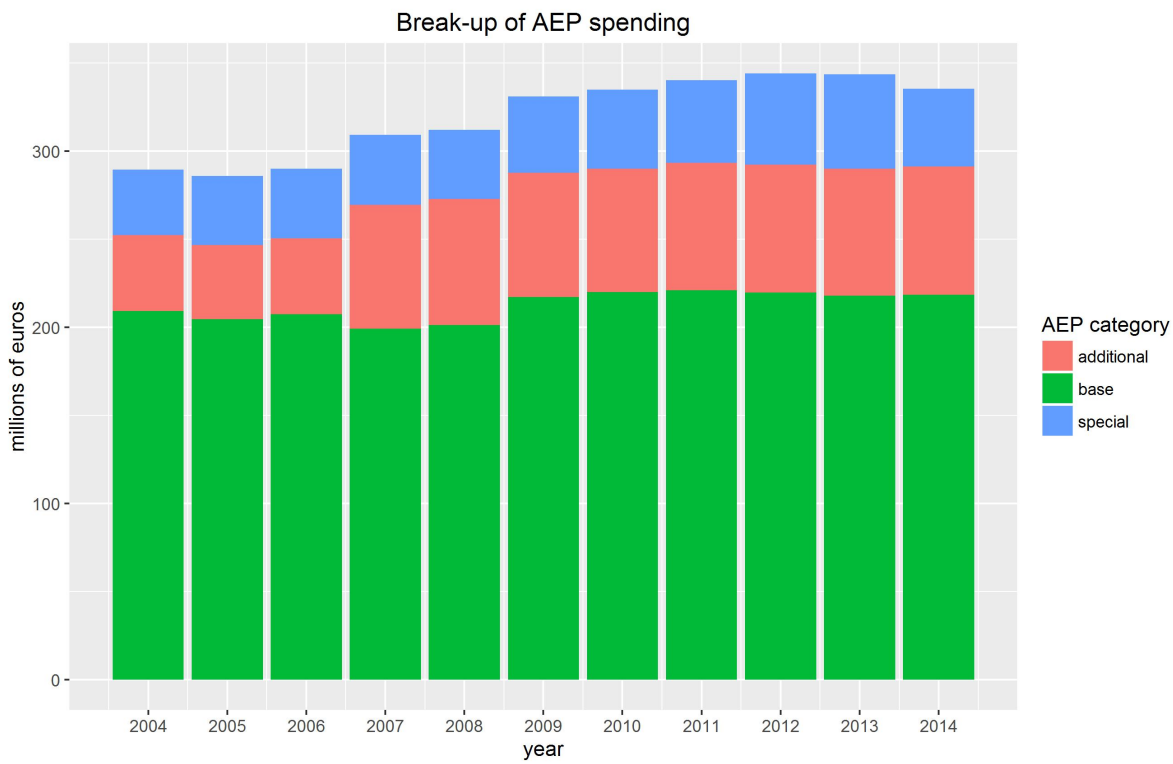

Figure 6: Average annual land area enrolled in "additional measures," second AEP period.

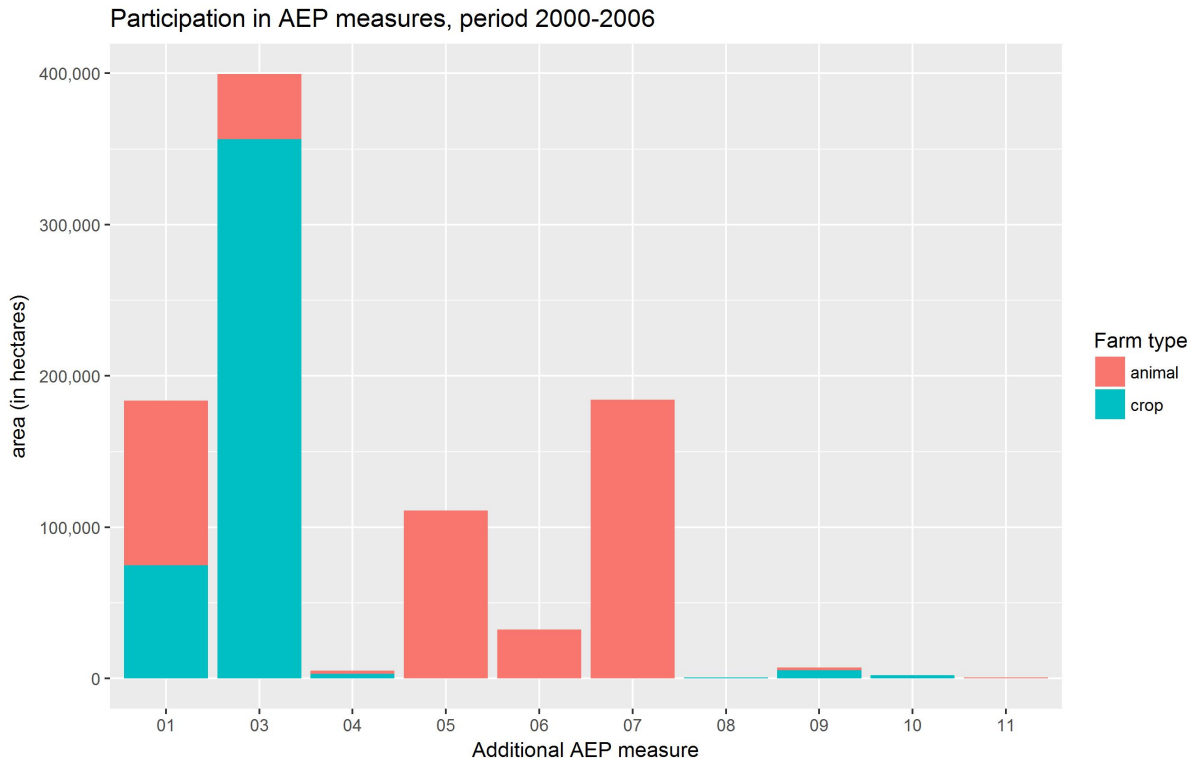

Figure 7: Average annual land area enrolled in "additional measures," third AEP period.

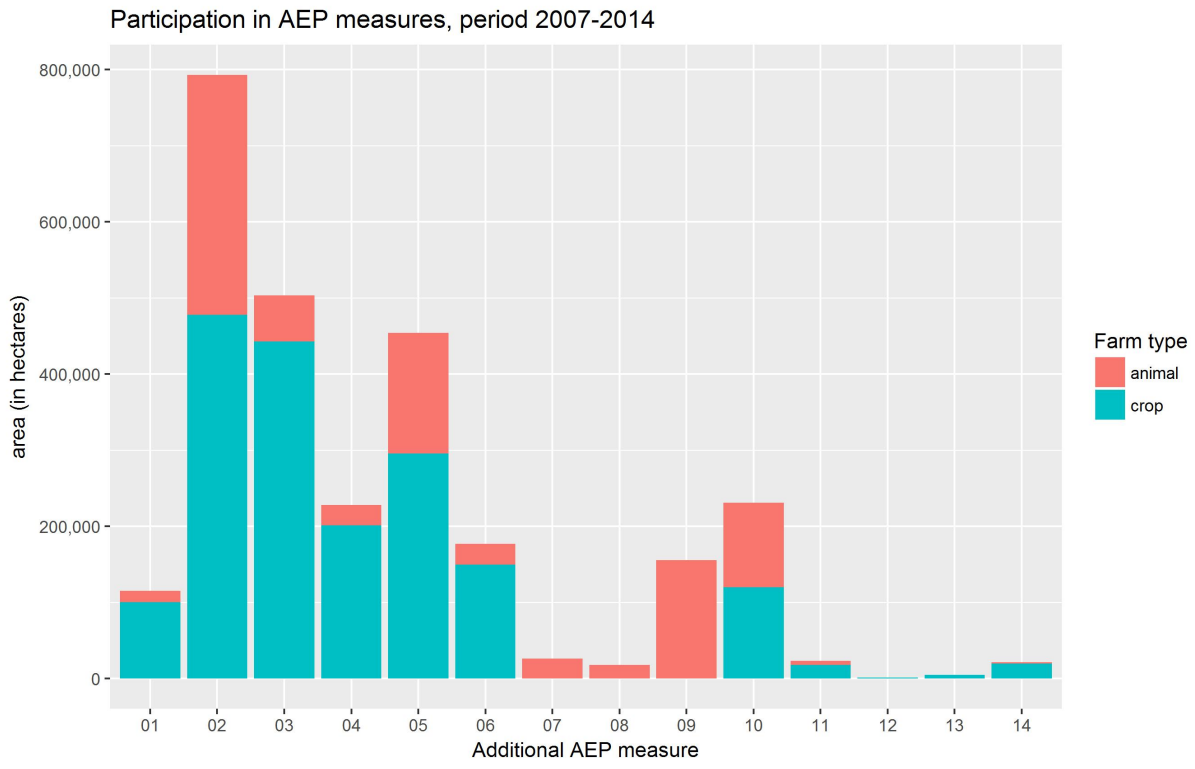

Figure 8: Average annual land area enrolled in "additional measure" combinations, second AEP period.

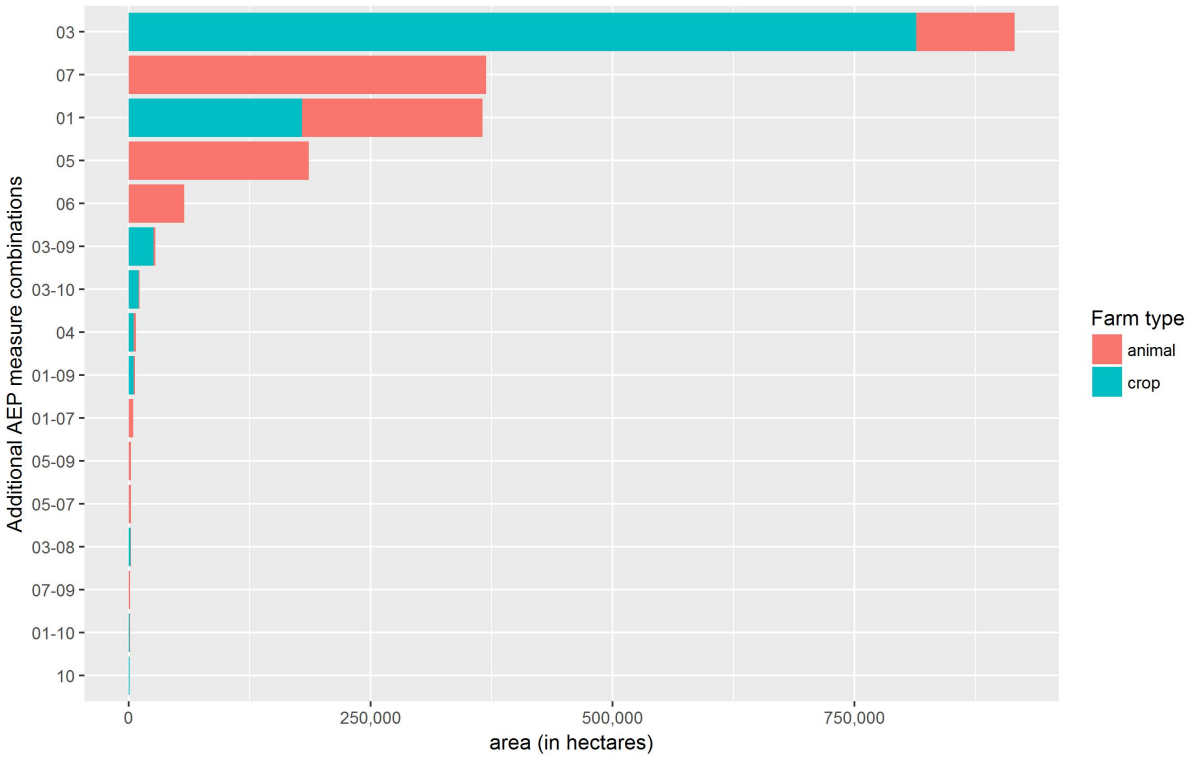

Figure 9: Average annual land area enrolled in "additional measure" combinations, third AEP period.

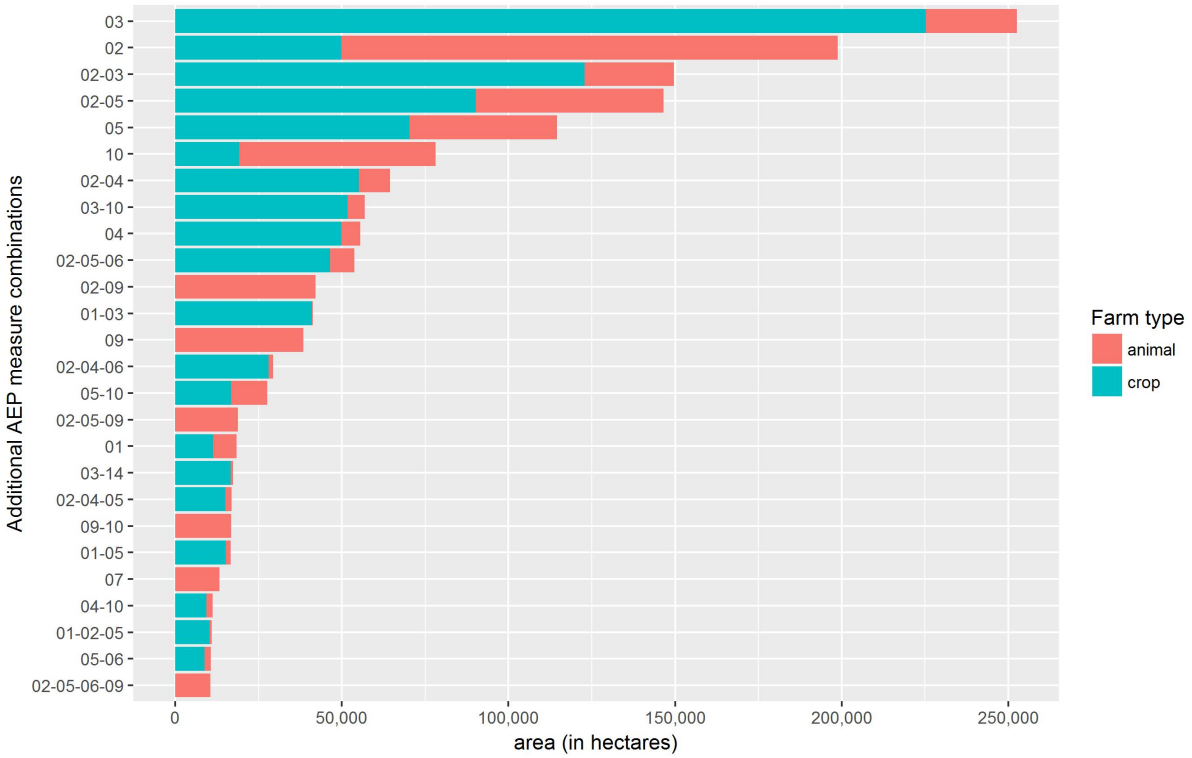

Table 1: First three moments of simulated sampling distributions.

		$I = 100$			$I = 1000$		
Parameter	Actual	Mean	Std. Dev.	Std. Skew	Mean	Std. Dev.	Std. Skew
β_{11}	0.25	0.24	0.33	0.30	0.21	0.15	-0.07
β_{21}	1.00	1.00	0.13	-0.01	1.00	0.04	-0.02
σ_{v1}	0.38	0.34	0.13	-0.31	0.39	0.05	-0.19
β_{21}	0.50	0.52	0.21	0.14	0.49	0.07	0.10
β_{22}	0.75	0.75	0.11	-0.13	0.75	0.03	0.03
σ_{v2}	0.22	0.18	0.08	0.22	0.22	0.03	0.03
γ_{21}	0.19	0.80	8.31	1.91	0.19	1.31	0.87
γ_{22}	-0.19	-1.00	3.67	-5.23	-0.26	0.22	-3.36
δ	0.80	8.90	90.74	5.42	0.64	7.50	4.07
σ_{u11}	0.45	0.64	0.50	2.44	0.68	0.32	1.56
σ_{u22}	0.32	0.40	0.23	0.79	0.40	0.14	1.59
σ_{u12}	0.00	-0.42	0.67	-1.67	-0.34	0.49	-1.93

Table 2: "Additional measures" enacted during second and third AEP periods.

Policy Number	Second Period (2000-2006)	Third Period (2007-2014)
1	More accurate fertilization	Reduced fertilization
2	-	More accurate nitrogen fertilization on arable crops
3	Plant cover in winter and reduced tillage	Plant cover in winter and reduced tillage
4	Biodiversity on farms	Plant cover in winter
5	Reduction in ammonia emissions	Intensified plant cover in winter
6	Improving the welfare of animals	Crop diversification
7	Treatment of washing water from milking rooms	Extensive grassland production
8	More accurate follow up of nutrients	Extensive grassland production, region C
9	Measuring soluble nitrogen	Spreading of manure during the growing season
10	Organic cover in weed control	Nutrient balance
11	Catchment of manure gases	Cultivation of catch plants
12	-	More accurate nitrogen fertilization of horticultural crops
13	-	Use of mulch in perennial horticultural crops
14	-	Use of pest monitoring methods

The official policy numbering across periods is not completely consistent with AEP practices.

Table 3: Summary statistics.

	Policy 3 (1,895 obs.)		Policy 2 (1,615 obs.)		Policy 2 & 3 (739 obs.)		Not Adopting (446 obs.)	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. De
Grain (log t)	147.99	160.17	79.44	78.75	145.65	150.05	59.18	52.41
Land (log ha)	86.58	72.10	44.25	36.20	73.93	57.64	29.73	22.08
Fertilizer (log t)	71.54	87.49	33.82	42.55	59.93	63.65	24.38	25.44
Machinery (log index)	419.53	619.78	206.74	290.12	377.18	538.10	143.10	212.42
Fuel (log hl)	60.78	35.59	31.86	38.03	57.91	68.33	21.07	26.12
SEU 1	0.36	0.48	0.13	0.34	0.21	0.41	0.03	0.16
SEU 2	0.55	0.50	0.15	0.36	0.25	0.43	0.17	0.37
SEU 3	0.08	0.27	0.41	0.49	0.28	0.45	0.56	0.50
SEU 4	0.02	0.12	0.30	0.46	0.27	0.44	0.25	0.43
Temperature (avg C)	14.01	0.98	13.66	0.93	13.88	0.94	13.59	0.91
Precipitation (avg C)	2.16	0.45	2.29	0.48	2.22	0.44	2.29	0.48
Growing Season (days)	153.57	11.74	145.78	15.42	146.93	15.54	144.86	14.75
Baltic	0.67	0.47	0.73	0.44	0.73	0.44	0.71	0.45
Manager's Age (years)	51.49	11.71	51.69	12.41	50.55	11.93	52.54	12.16
CAP Subsidy (EUR 1000)	18.901	16.983	8.530	6.958	14.808	12.512	5.667	4.157
LFA Subsidy (EUR 1000)	16.968	13.812	9.251	7.537	15.136	11.593	6.107	5.302
Debts/Assets	1.04	7.82	0.68	1.34	0.75	1.13	0.52	1.21
Municipal Policy 2 (avg rate)	0.57	0.17	0.28	0.21	0.48	0.20	0.27	0.17
Municipal Policy 3 (avg rate)	0.22	0.17	0.63	0.27	0.55	0.27	0.49	0.24
Municipal No Add./Sp. (avg rate)	0.03	0.07	0.10	0.11	0.0.08	0.10	0.25	0.17

Table 4: Log-log (I) and SFA (II) estimates (production stage reduced form).

	Policy 3		Policy 2		Policy 2 & 3		Not Adopting	
	I	II	I	II	I	II	I	II
Constant	**14.380**	**8.806**	**13.455**	**10.855**	**11.564**	**7.927**	0.188	1.094
Land	**0.846**	**0.890**	**0.823**	**0.900**	**0.908**	**0.891**	**0.802**	**0.862**
Fertilizer	**0.095**	**0.075**	**0.112**	**0.078**	**0.087**	**0.079**	**0.061**	**0.059**
Machinery	-0.020	-0.013	0.008	0.011	0.014	0.006	-0.011	**0.038**
Fuel	0.030	**0.040**	0.003	0.007	0.015	0.038	0.024	0.013
2008	**-0.170**	-0.051	**-0.271**	**-0.179**	-0.164	-0.070	0.038	0.068
2009	-0.044	0.037	0.019	0.015	-0.117	-0.086	0.052	0.129
2010	**-0.171**	**-0.173**	0.063	0.080	-0.107	-0.067	-0.147	-0.046
2011	0.029	0.010	**0.139**	**0.109**	0.163	0.133	0.069	0.088
2012	**-0.154**	**-0.144**	**-0.117**	**-0.124**	-0.035	0.028	0.159	0.120
2013	-0.149	-0.117	**-0.243**	**-0.143**	**-0.515**	**-0.400**	**-0.751**	**-0.416**
SEU 2	**0.076**	-0.025	**0.141**	0.004	**0.243**	0.066	**0.362**	0.139
SEU 3	-0.011	-0.008	**-0.181**	**-0.262**	-0.131	**-0.185**	**0.388**	0.101
SEU 4	**-0.307**	**-0.275**	**-0.277**	**-0.338**	-0.153	**-0.245**	0.320	0.021
Temperature	**-3.040**	**-1.794**	**-3.013**	**-2.194**	**-2.305**	-1.384	0.361	-0.139
Precipitation	-0.104	-0.061	0.014	0.046	-0.344	-0.269	-0.135	0.031
Growing Season	**-1.105**	-0.539	**-0.943**	**-0.754**	**-0.944**	-0.543	-0.056	0.092
σ_v	0.636	**0.237**	0.569	**0.161**	0.644	**0.224**	0.591	**0.118**
σ_u		**0.962**		**0.851**		**0.952**		**0.851**
R^2	0.54		0.60		0.59		0.54	

Estimates in **bold** are significant at 5%.

Table 5: Multinomial logit estimates (selection stage reduced form).

	Policy 3	Policy 2	Policy 2 & 3
Baltic	0.141	0.073	0.169
Debts/Assets	**0.244**	0.089	0.098
Manager's Age	0.001	-0.001	-0.004
CAP Subsidy	-0.017	**-0.086**	-0.032
LFA Subsidy	0.062	**0.113**	**0.082**
Municipal Policy 2	**2.934**	**-1.632**	**4.399**
Municipal Policy 3	**-3.789**	**-1.758**	**3.243**
Municipal No Add./Spec.	**-8.752**	**-6.939**	**-2.578**

Base case is non-adoption. Pseudo $R^2 = 0.35$.
Estimates for production variables included in this equation not shown.
Estimates in **bold** are significant at 5%.

Table 6: Production stage (joint estimates).

	Policy 3	Policy 2	Policy 2 & 3	Not Adopting
Constant	**14.393**	**13.469**	**11.578**	0.196
Land	**0.861**	**0.852**	**0.925**	**0.800**
Fertilizer	**0.102**	**0.102**	**0.095**	**0.062**
Machinery	-0.012	0.014	0.011	-0.010
Fuel	**0.036**	0.009	0.029	0.019
2008	**-0.175**	**-0.238**	-0.159	0.045
2009	0.000	-0.007	-0.094	0.054
2010	-0.084	**0.134**	-0.028	-0.142
2011	0.090	**0.158**	**0.214**	0.067
2012	**-0.168**	**-0.154**	-0.014	0.156
2013	-0.024	-0.093	**-0.319**	**-0.741**
SEU 2	-0.014	0.001	**0.131**	**0.362**
SEU 3	-0.091	**-0.286**	-0.151	0.390
SEU 4	**-0.339**	**-0.361**	**-0.233**	0.320
Temperature	**-2.993**	**-2.953**	**-2.268**	0.382
Precipitation	-0.096	0.023	**-0.332**	-0.128
Growing Season	**-1.041**	**-0.878**	**-0.873**	-0.017
σ_v	**0.321**	**0.207**	**0.288**	0.529*

Estimates in **bold** are significant at 5%.
* Standard error is numerically unstable.

Table 7: Selection stage (joint estimates).

	Policy 3	Policy 2	Policy 2 & 3
Baltic	0.151	0.006	0.175
Debts/Assets	**0.246**	0.090	0.101
Manager's Age	0.002	0.000	-0.002
CAP Subsidy	-0.013	-0.082	-0.030
LFA Subsidy	0.064	**0.114**	**0.085**
Municipal Policy 2	**2.825**	**-1.742**	**4.334**
Municipal Policy 3	**-3.797**	**1.752**	**3.333**
Municipal No Add./Sp.	**-8.853**	**-7.028**	**-2.557**
u_j	**-0.489**	**-0.489**	**-0.489**

Base case is non-adoption.
Estimates for production variables included in this equation not shown.
Estimates in **bold** are significant at 5%.

Table 8: $\Sigma_u^{1/2}$ (joint estimates).

	Policy 3	Policy 2	Policy 2 & 3	Not Adopting
Policy 3	**1.975**			
Policy 2	**-0.625**	**2.610**		
Policy 2 & 3	-0.363	-0.535	**2.279**	
Not Adopting	-0.301	-0.877*	-0.673*	0.577*

Estimates in **bold** are significant at 5%.

* Standard error is numerically unstable.