

Appendix A: Bayesian Estimation Methods Using Orthogonal Reparameterization

To explain the method introduced by Dhaene and Jochmans (2016) in our setting, we focus for simplicity on the extended FE ECM (5) as applied to a balanced panel with I experts, each providing estimates her primary county only, and T periods. In that case, FE ECM (5) for experts' FEs can written more compactly as:

$$(A1) \quad y_{i,t} = \alpha_i + \underline{z}_{i,t}^T \underline{\theta} + e_{i,t},$$

for $i = 1, \dots, I$, and $t = 1, \dots, T$. In this expression, $\underline{z}_{i,t}^T \equiv [y_{i,t-1}^T, \underline{x}_{c(i),t}^T]$, $\underline{y}_{i,t-}^T \equiv [y_{i,t-1}, \dots, y_{i,t-p}]$, $\underline{x}_{c(i),t}^T \equiv [x_{c(i),t}, \dots, x_{c(i),t-q}]$, and $\underline{\theta} \equiv [\underline{\rho}^T, \underline{\phi}^T]^T$ is a vector of parameters with $\underline{\rho}^T \equiv [\rho_1, \dots, \rho_p]$ for $p \geq 1$ and $\underline{\phi}^T \equiv [\phi_1, \dots, \phi_q]$ for $q \geq 0$. The parameters in equation (5) can be recovered from the ones in regression (A1) as $\beta_y = -1 + \sum_{s=1}^p \rho_s$, $\delta_{n_y} = -\sum_{s=n_y+1}^{N_y} \rho_s$, $\gamma_x = \phi_1$, $\beta_x = \sum_{s=1}^q \phi_s$, and $\delta_{n_x} = -\sum_{s=n_x+2}^{N_x} \phi_s$.

Given that we are mainly interested in the estimates of the common parameters $\underline{\theta}$ rather than the estimates of the FEs $\underline{\alpha}^T \equiv [\alpha_1, \dots, \alpha_I]$, the orthogonal reparameterization of the FEs allows one to integrate the FEs out of the likelihood function, so that the common parameters can be estimated independently of the (reparameterized) FEs (Pickup et al. 2017).¹ Here, we follow Dhaene and Jochmans (2016) by reparameterizing FEs as $\eta_i \equiv \alpha_i \exp[-(T-1) a(\underline{\rho})]$, where function $a(\underline{\rho})$ of the autoregression coefficients is given by

$$(A2) \quad a(\underline{\rho}) \equiv -\sum_{S \in \mathcal{S}} \sum_{t=|S|}^{T-1} \frac{T-t}{T(T-1)} \sum_{k \in \mathcal{K}_S: \tau^T k = t} \frac{(t^T k - 1)!}{k_1! \dots k_p!} \rho_S^{k_S},$$

where S is the family of nonempty subsets of $\{1, \dots, p\}$, $|S|$ represents the sum of S 's elements, $K_S \equiv \{k \in P^p \mid k_j > 0 \Leftrightarrow j \in S\}$, $\rho_S \equiv (\rho_{j \in S})$ is the subvector of ρ determined by S , and $k_S \equiv (k_{j \in S})$ is defined analogously.

With $e_{i,t} \sim N(0, \sigma^2)$, and conditional on the initial values $\underline{y}_i^0 \equiv [y_{i,1-p}, \dots, y_{i,0}]^T$, the following likelihood function is obtained after integrating the FEs assuming independent uniform priors for η_i (Dhaene and Jochmans 2016):²

$$(A3) \quad l(\underline{\theta}, \sigma | \text{data}) \propto \sigma^{-I(T-1)} \exp[-Q^2(\underline{\theta})/(2\sigma^2)] \exp[-I(T-1)a(\underline{\rho})],$$

where $Q^2(\underline{\theta}) \equiv \sum_{i=1}^I (\underline{y}_i - \underline{z}_i \underline{\theta})^T \underline{H} (\underline{y}_i - \underline{z}_i \underline{\theta})$, $\underline{y}_i \equiv [y_{i,1}, \dots, y_{i,T}]^T$, $\underline{y}_i \equiv [y_{i,1}, \dots, y_{i,T}]^T$, $\underline{x}_{c(i)} \equiv [x_{c(i),1}, \dots, x_{c(i),T}]^T$, $\underline{z}_i \equiv [\underline{y}_i, \underline{x}_{c(i)}]$, $\underline{H} \equiv \underline{I}_T - T^{-1} \underline{1} \underline{1}^T$, \underline{I}_T is the $(T \times T)$ identity matrix, and $\underline{1}$ is a T -vector of ones. This likelihood, in conjunction with weakly informative priors for $\{\underline{\theta}, \sigma\}$, provides the basis for our Bayesian estimation. More specifically, our priors for $\underline{\theta}$ are Student's t with $\nu = 3$ degrees of freedom, location parameter $\hat{\mu} = 0$, and scaling parameter $\hat{\sigma} = 3/\sqrt{3}$ (so that priors have zero mean a standard deviation of $3 = \hat{\sigma} \sqrt{\nu/(\nu-2)}$), and the prior for σ is Half-Cauchy(0, 2.5).³

Intuitively, $Q^2(\underline{\theta})$ is the sum of squared deviations after subtracting the expert-specific means from the data. Hence, the likelihood function (A3) can be interpreted as consisting of two components. The first component, comprising the first two terms on the right-hand side of (A3), $\sigma^{-I(T-1)} \exp[-Q^2(\underline{\theta})/(2\sigma^2)]$, is the standard likelihood. If estimates were based solely on this first

component, they would exhibit Nickell bias. The second component, $\exp[-I(T-1)a(\underline{\rho})]$, is an extra term that "corrects" for the Nickell bias. The likelihood function (A3) also makes it clear that estimation of the common parameters in (A1) does not require estimating the FEs.

Turning attention to the errors-in-variables model (9), the likelihood function for $\{\mu_x, \sigma_x\}$ is

$$(A4) \quad l(\mu_x, \sigma_x | \text{data}) \propto \sigma_x^{CT} \exp[-\sum_{c=1}^C \sum_{t=1}^T (\hat{x}_{c,t} - \mu_x)^2 / (2 \sigma_x^2)],$$

where $\sigma_x^2 \equiv \sigma_x^2 + \sigma_\varepsilon^2$, and C is the number of counties. Since the expectation of the prevailing price $x_{c,t}$ is conditional on $\{\hat{x}_{c,t}, \mu_x, \sigma_x, \sigma_\varepsilon\}$ is $E(x_{ct} | \hat{x}_{c,t}, \mu_x, \sigma_x, \sigma_\varepsilon) = \mu_x + \sigma_x^2 / \sigma_x^2 (\hat{x}_{c,t} - \mu_x)$, the likelihood (A4) does not provide enough information to identify this expectation. Hence, we achieve identification by adopting a prior distribution for the ratio $\sigma_\varepsilon / \sigma_x$, which we take to be $\sigma_\varepsilon / \sigma_x \sim 0.5 \text{ Beta}(\alpha=3, \beta=3)$. This prior implies that the standard deviation of the noise is symmetrically distributed between 0% and 50% of the standard deviation of the prevailing price, with an average of 25% and 67% probability of being between 15% and 35% of the standard deviation of the prevailing price.⁴ We complete the setup for the Bayesian estimation by postulating the priors $\mu_x \sim \text{Student-}t(\nu=3, \hat{\mu} = 0, \hat{\sigma} = 2.5/\sqrt{3})$, and $\sigma_x \sim \text{Half-Cauchy}(0, 2.5)$. In summary, our Bayesian setup consists of the likelihood functions (A3) and (A4) for $\{\underline{\theta}, \sigma\}$ and $\{\mu_x, \sigma_x\}$, respectively, and the aforementioned σ_ε priors for $\{\underline{\theta}, \sigma, \mu_x, \sigma_x, \sigma_\varepsilon / \sigma_x\}$. We estimate the generalized regression (8) in a similar manner, with $\text{Student-}t(\nu=3, \hat{\mu} = 0, \hat{\sigma} = 3/\sqrt{3})$

priors for all of the slope coefficients, and a $\sigma_u \sim \text{Half-Cauchy}(0, 2.5)$ prior for the standard deviation of the residuals.

Appendix B: Estimation Results without Correction for Nickell Bias

Table B.1. Estimates of Error Correction Model with Individual Expert Fixed Effects but without Correction for Nickell Bias,
 Assuming that the Median of Experts' Opinions is a Proxy for the Unobservable Prevailing Land Value

	County Level			CRD Level		
	High-Quality	Medium-Quality	Low-Quality	High-Quality	Medium-Quality	Low-Quality
y_{t-1}	-1.069*** (.036) [-1.140, -1.001]	-1.010*** (.034) [-1.076, -.941]	-.833*** (.032) [-.897, -.771]	-1.068*** (.036) [-1.139, -.999]	-1.009*** (.034) [-1.077, -.941]	-.832*** (.031) [-.893, -.770]
x_{t-1}	1.098*** (.066) [.986, 1.239]	1.054*** (.063) [.943, 1.189]	.850*** (.057) [.747, .971]	1.096*** (.065) [.984, 1.238]	1.052*** (.063) [.944, 1.188]	.852*** (.057) [.750, .975]
Δx_t	.881*** (.047) [.805, .983]	.851*** (.048) [.769, .955]	.797*** (.047) [.714, .896]	.881*** (.048) [.802, .985]	.850*** (.048) [.770, .953]	.798*** (.047) [.717, .901]
Δy_{t-1}	.086*** (.026) [.034, .136]	.056** (.026) [.005, .108]	-.003 (.025) [-.053, .047]	.086*** (.026) [.036, .134]	.056** (.026) [.007, .106]	-.002 (.026) [-.052, .048]
Δx_{t-1}	-.086** (.036) [-.157, -.017]	-.095*** (.036) [-.166, -.026]	-.043 (.035) [-.111, .026]	-.087*** (.035) [-.156, -.019]	-.093*** (.035) [-.162, -.024]	-.044 (.035) [-.114, .023]
Intercept	310 individual expert FEs	310 individual expert FEs	310 individual expert FEs	310 individual expert FEs	310 individual expert FEs	310 individual expert FEs
Long-Run Elasticity	1.028*** (.049) [.954, 1.134]	1.043*** (.050) [.967, 1.154]	1.021*** (.053) [.936, 1.141]	1.026*** (.049) [.955, 1.137]	1.043*** (.051) [.967, 1.157]	1.024*** (.054) [.935, 1.141]
Std. Deviation of Residuals	.150*** (.003) [.145, .155]	.172*** (.003) [.167, .178]	.216*** (.004) [.209, .223]	.150*** (.003) [.145, .155]	.172*** (.003) [.167, .178]	.216*** (.004) [.208, .224]
Bayesian R²	.855 (.005) [.844, .864]	0.830 (.006) [.818, .841]	.758 (.009) [.738, .775]	.855 (.005) [.844, .864]	0.830 (.006) [.818, .842]	.756 (.010) [.738, .776]

Observations	1,989	1,989	1,989	1,989	1,989	1,989
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*** (**, *) Different from zero at the 1% (5%, 10%) level of significance, based on the respective 99% (95%, 90%) Credible Interval.

Note: Standard deviations are shown within parentheses, and lower and upper bounds of 95% credible intervals are shown within brackets.

Appendix C: Robustness Checks using Alternative Prevailing Price Proxies and Different Estimation Samples

Table C.1 Robustness Checks for FE ECMs Assuming Unobservable Prevailing Land Values are Proxied by the CRD-level Cropland Value Estimates from the Realtor Land Institute Survey or Farmland Value Estimates from Iowa State University Survey

	Prevailing Value Proxy: Realtor Land Institute			Prevailing Value Proxy: Iowa State University		
	High-Quality	Medium-Quality	Low-Quality	High-Quality	Medium-Quality	Low-Quality
y_{t-1}	-.727*** (.040) [-.807, -.646]	-.665*** (.038) [-.740, -.590]	-.511*** (.035) [-.579, -.444]	-.790*** (.038) [-.863, -.716]	-.751*** (.036) [-.821, -.681]	-.629*** (.033) [-.693, -.565]
x_{t-1}	.704*** (.059) [.591, .828]	.644*** (.058) [.534, .758]	.489*** (.058) [.377, .606]	.831*** (.058) [.726, .952]	.777*** (.056) [.673, .895]	.653*** (.052) [.559, .763]
Δx_t	1.123*** (.066) [1.010, 1.266]	.974*** (.063) [.862, 1.102]	.759*** (.062) [.644, .888]	.932*** (.060) [.826, 1.057]	.808*** (.059) [.703, .934]	.763*** (.067) [.638, .899]
Δy_{t-1}	-.029 (.027) [-.082, .026]	-.078*** (.027) [-.131, -.026]	-.108*** (.026) [-.158, -.057]	-.028 (.026) [-.080, .021]	-.053** (.025) [-.102, -.003]	-.054** (.025) [-.103, -.006]
Δx_{t-1}	-.048 (.046) [-.136, .040]	.006 (.050) [-.092, .102]	.083 (.055) [-.024, .192]	.156*** (.047) [.064, .249]	.165*** (.051) [.067, .266]	.231*** (.061) [.112, .351]
Intercept	310 individual expert FEs	310 individual expert FEs	310 individual expert FEs	310 individual expert FEs	310 individual expert FEs	310 individual expert FEs
Long-Run Elasticity	.967*** (.050) [.883, 1.074]	.967*** (.054) [.872, 1.080]	.955*** (.074) [.814, 1.102]	1.053*** (.052) [.972, 1.167]	1.035*** (.054) [.949, 1.153]	1.037*** (.061) [.932, 1.166]
Std. Deviation	.174*** (.003)	.195*** (.003)	.244*** (.004)	.164*** (.003)	.187*** (.003)	.233*** (.004)

of Residuals	[.169, .181]	[.189, .202]	[.235, .252]	[.159, .170]	[.181, .194]	[.225, .241]
Bayesian R²	.782 (.008)	.744 (.009)	.659 (.012)	.816 (.006)	.783 (.008)	.704 (.011)
	[.766, .796]	[.726, .761]	[.634, .682]	[.803, .828]	[.767, .797]	[.682, .725]
Observations	1,989	1,989	1,989	1,989	1,989	1,989

*** (**, *) Different from zero at the 1% (5%, 10%) level of significance, based on the respective 99% (95%, 90%) Credible Interval.

Note: The table reports posterior means, posterior standard deviations (within parentheses), and 95% credible intervals [within brackets].

Table C.2 Robustness Checks for FE ECMs for High-Quality Land under Selected Types of Experts and Periods

	Prevailing Value Proxy: Experts' County Median			Prevailing Value Proxy: Experts' CRD Median		
	Experts with 11 Annual Responses	Farm managers, rural appraisers and ag lenders only	2005-2013	Experts with 11 Annual Responses	Farm managers, rural appraisers and ag lenders only	2005-2013
y_{t-1}	-0.957*** (.051) [-1.055, -.858]	-0.783*** (.067) [-.914, -.653]	-0.940*** (.048) [-1.029, -.843]	-0.956*** (.051) [-1.051, -.857]	-0.784*** (.065) [-.910, -.653]	-0.941*** (.048) [-1.032, -.844]
x_{t-1}	.984*** (.074) [.849, 1.138]	.801*** (.082) [.646, .967]	.992*** (.069) [.865, 1.136]	.983*** (.074) [.841, 1.134]	.801*** (.080) [.649, .963]	.993*** (.069) [.861, 1.132]
Δx_t	.912*** (.058) [.809, 1.035]	.871*** (.054) [.778, .985]	.874*** (.049) [.789, .978]	.911*** (.058) [.808, 1.037]	.872*** (.054) [.778, .987]	.875*** (.051) [.790, .981]
Δy_{t-1}	.049 (.036) [-.021, .120]	.018 (.048) [-.076, .113]	.070** (.031) [.008, .129]	.048 (.035) [-.019, .118]	.018 (.047) [-.075, .111]	.070** (.032) [.006, .133]
Δx_{t-1}	-.016 (.053) [-.123, .086]	-.053 (.057) [-.166, .055]	-.076* (.046) [-.164, .014]	-.015 (.052) [-.120, .087]	-.053 (.056) [-.160, .060]	-.076 (.047) [-.168, .016]
Intercept	113 individual expert FEs	107 individual expert FEs	297 individual expert FEs	113 individual expert FEs	107 individual expert FEs	297 individual expert FEs
Long-Run Elasticity	1.029*** (.052) [.947, 1.142]	1.022*** (.053) [.938, 1.137]	1.055*** (.050) [.976, 1.165]	1.028*** (.053) [.948, 1.146]	1.022*** (.053) [.939, 1.137]	1.055*** (.052) [.975, 1.166]
Std. Deviation of Residuals	.181*** (.004) [.173, .190]	.122*** (.004) [.115, .129]	.148*** (.003) [.143, .154]	.181*** (.004) [.173, .191]	.122*** (.004) [.114, .129]	.148*** (.003) [.142, .154]
Bayesian R²	.809 (.009) [.790, .826]	.892 (.006) [.878, .904]	.866 (.005) [.856, .877]	.809 (.010) [.790, .827]	.892 (.006) [.878, .904]	.867 (.006) [.856, .877]
Observations	990	717	1,583	990	717	1,583

*** (**, *) Different from zero at the 1% (5%, 10%) level of significance, based on the respective 99% (95%, 90%) Credible Interval.

Note: The table reports posterior means, posterior standard deviations (within parentheses), and 95% credible intervals [within brackets].

Table C.3 Robustness Checks for FE ECMs for Selected Counties Based on the Total Number of Expert Responses Used to Construct CRD Medians

	Experts' CRD Median in the Top-Third Quantile Based on Number of Expert Responses			Experts' CRD Medians in the Bottom-Third Quantile Based on Number of Expert Responses		
	High-Quality	Medium-Quality	Low-Quality	High-Quality	Medium-Quality	Low-Quality
y_{t-1}	-.839*** (.077) [-.988, -.685]	-.719*** (.071) [-.858, -.574]	-.573*** (.064) [-.697, -.445]	-.935*** (.071) [-1.069, -.792]	-.873*** (.073) [-1.016, -.731]	-.641*** (.072) [-.780, -.498]
x_{t-1}	.852*** (.093) [.672, 1.038]	.739*** (.087) [.572, .920]	.578*** (.081) [.422, .739]	.947*** (.090) [.772, 1.134]	.899*** (.096) [.717, 1.095]	.634*** (.096) [.450, .829]
Δx_t	.932*** (.070) [.806, 1.079]	.936*** (.074) [.796, 1.084]	.885*** (.077) [.743, 1.043]	.847*** (.059) [.741, .972]	.842*** (.063) [.728, .978]	.781*** (.064) [.664, .914]
Δy_{t-1}	.012 (.051) [-.086, .110]	-.027 (.049) [-.124, .071]	-.079 (.050) [-.180, .017]	.012 (.048) [-.083, .104]	-.052 (.049) [-.148, .044]	-.138*** (.052) [-.238, -.035]
Δx_{t-1}	.030 (.070) [-.103, .166]	.123 (.078) [-.029, .277]	.085 (.074) [-.058, .228]	-.038 (.064) [-.162, .086]	-.034 (.067) [-.166, .096]	.098 (.070) [-.039, .236]
Intercept	125 individual expert FEs	125 individual expert FEs	125 individual expert FEs	125 individual expert FEs	125 individual expert FEs	125 individual expert FEs
Long-Run Elasticity	1.015*** (.056) [.921, 1.135]	1.027*** (.061) [.922, 1.159]	1.009*** (.083) [.857, 1.189]	1.012*** (.054) [.926, 1.132]	1.029*** (.060) [.929, 1.159]	.988*** (.080) [.839, 1.155]
Std. Deviation of Residuals	.161*** (.005) [.151, .172]	.172*** (.006) [.162, .183]	.223*** (.007) [.209, .238]	.152*** (.005) [.143, .161]	.180*** (.006) [.169, .191]	.224*** (.008) [.211, .239]
Bayesian R²	.828 (.011) [.805, .849]	.808 (.012) [.783, .830]	.707 (.019) [.667, .742]	.857 (.010) [.837, .874]	.832 (.012) [.808, .854]	.780 (.016) [.745, .810]
Observations	646	646	646	630	630	630

*** (**, *) Different from zero at the 1% (5%, 10%) level of significance, based on the respective 99% (95%, 90%) Credible Interval.

Note: The table reports posterior means, posterior standard deviations (within parentheses), and 95% credible intervals [within brackets].

Grouped Endnotes for Appendix A

¹ Of course, the reparameterization retains the distinguishing properties of FEs (i.e., being time-invariant and expert-specific).

² Dhaene and Jochmans (2016) demonstrate that, under the stated assumptions underlying (A3), independent and uniform priors on $\{\eta_i, \underline{\theta}, \ln(\sigma^2)\}$ lead to the following posterior distribution for $\{\underline{\theta}, \sigma\}$:

$$f(\underline{\theta}, \sigma | \text{data}) \propto \sigma^{I(T-1)-2} \exp[-I(T-1) a(\underline{\rho}) - Q^2(\underline{\theta})/(2 \sigma^2)].$$

Given such priors for $\{\underline{\theta}, \ln(\sigma^2)\}$, this posterior implies that the likelihood for $\{\underline{\theta}, \sigma\}$ is (A3).

³ Student's t distributions are used instead of the more popular Normal distributions because Gelman (<https://github.com/stan-dev/stan/wiki/Prior-Choice-Recommendations>) notes that the latter are not a robust prior and therefore not recommended as weakly informative.

⁴ This prior seems reasonable for the present data. The estimates of σ_{ξ} for high-, medium-, and low-quality land using county (CRD) values are respectively 0.453, 0.465, and 0.467 (0.426, 0.426, and 0.425). The standard deviation σ_{ε} is unobservable; however, the averages of the standard deviations of the estimated county (CRD) log-price means provide crude estimates of σ_{ε} . Such averages are equal to 0.082, 0.095, and 0.130 (0.035, 0.039, and 0.049) for high-, medium-, and low-quality farmland, respectively.