SUPPLEMENT TO "MARKET ENTRY COSTS, PRODUCER HETEROGENEITY, AND EXPORT DYNAMICS"

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BAYESIAN MCMC ESTIMATION

THE MEANS AND STANDARD DEVIATIONS reported in Table 1 are constructed as $\bar{\theta} = \frac{1}{S}\sum_{s=1}^{S} \theta^s$ and $\sqrt{\frac{1}{S}\sum_{s=1}^{S}(\theta^s - \bar{\theta}) \cdot (\theta^s - \bar{\theta})'}$, respectively, where $(\theta^1, \ldots, \theta^s, \ldots, \theta^S)$ is a Monte Carlo Markov chain (MCMC) of S draws from the posterior distribution $P(\theta \mid D)$. We use MCMC techniques to calculate the moments of $P(\theta \mid D)$ because they have no closed-form representation. The type of MCMC sampling we use—random walk, Metropolis–Hastings—allows us to simulate draws from $P(\theta \mid D)$ without having to sample from $P(\theta \mid D)$ directly (Gilks, Richardson, and Speigelhalter (1996)).

Before describing our sampling algorithm, several comments are in order. First, we generate the chain in terms of a monotonic transformation of the parameter vector $\tilde{\theta} = b(\theta)$ and we recover $(\theta^1, \ldots, \theta^s, \ldots, \theta^S)$ from $(\tilde{\theta}^1, \ldots, \tilde{\theta}^s, \ldots, \tilde{\theta}^S)$ by inverting this transformation.[1] This transformation is not necessary, but it helps the chain to "mix" well; that is, to move quickly through the support of $P(\theta \mid D)$.

Second, we use a Metropolis–Hastings single-component updating algorithm. To do so, we break θ^s into blocks, $\theta^s = (\theta_1^s, \theta_2^s, \ldots, \theta_8^s)$; then we update these blocks sequentially. The block definitions reflect the structure of the model: $\theta_1 = \Psi$, $\theta_2 = \Lambda_x$, $\theta_3 = \Sigma_\omega$, $\theta_4 = \Gamma$, $\theta_5 = \Sigma_\varepsilon$, $\theta_6 = \boldsymbol{\eta}$, $\theta_7 = (\upsilon, \rho, \sigma_\xi)$, and $\theta_8 = \varsigma$. (In terms of the transformed parameters, the blocks are $\tilde{\theta}^s = (\tilde{\theta}_1^s, \tilde{\theta}_2^s, \ldots, \tilde{\theta}_8^s)$.) This allows us to better control acceptance rates, which in turn determines how quickly the chain moves through the support of $P(\theta \mid D)$. Given this single-component approach, the Metropolis–Hastings algorithm involves the following steps:

1. Set $s = 0$, $i = 1$, and choose an arbitrary vector of initial values, $\theta^0 = (\theta_1^0, \theta_2^0, \ldots, \theta_8^0)$. From this, construct the transformed vector $\tilde{\theta}^0 = b(\theta^0)$. Any $\theta^0 \in \{\theta \mid P(\theta \mid D) > 0\}$ will do; experimentation with alternative initial vectors is advisable.

2. Draw a candidate new value for subvector i from the random walk process $\tilde{\theta}_i^* = \tilde{\theta}_i^s + \vartheta_i^s$, where ϑ_i^s is a conformable vector of zero-mean, multivariate normal shocks with covariance matrix Σ_{ϑ_i}. This covariance matrix is

[1] Specifically, $\theta_j = \exp(\tilde{\theta}_j)$ for variances, $\theta_j = \exp(\tilde{\theta}_j) + 1$ for demand elasticities, and $\theta_j = \tilde{\theta}_j$ for all other parameters. These transformations reflect our lognormal priors for variances and demand elasticities.

chosen once at the beginning of the simulation; its magnitude determines acceptance rates.

3. Define the vector $\tilde{\theta}^s_{-i} = (\tilde{\theta}^{s+1}_1, \ldots, \tilde{\theta}^{s+1}_{i-1}, \tilde{\theta}^s_{i+1}, \ldots, \tilde{\theta}^s_8)$ to include all but the ith subvector of $\tilde{\theta}^s$, with the first $i-1$ components already updated for the sth iteration and the remaining $i+1$ through 8th components yet to be updated. Then construct the probability

$$\alpha^s_i = \min\left(\frac{P(\theta^*_i \mid \theta^s_{-i}, D)}{P(\theta^s_i \mid \theta^s_{-i}, D)}, 1\right)$$

and update the ith block of the parameter vector according to

$$(\theta^{s+1}_i, \theta^s_{-i}) = \begin{cases} (\theta^*_i, \theta^s_{-i}) & \text{with probability } \alpha^s_i, \\ (\theta^s_i, \theta^s_{-i}) & \text{with probability } 1-\alpha^s_i. \end{cases}$$

Given that

$$P(\theta_i \mid \theta^s_{-i}, D) = \frac{P(\theta^s_i, \theta^s_{-i} \mid D)}{\int_{\theta_i} P(\theta_i, \theta^s_{-i} \mid D)\, d\theta_i}$$

and

$$P(\theta^*_i \mid \theta^s_{-i}, D) = \frac{P(\theta^*_i, \theta^s_{-i} \mid D)}{\int_{\theta_i} P(\theta_i, \theta^s_{-i} \mid D)\, d\theta_i},$$

the ratio of probabilities needed to construct α^s_i is simply the posterior evaluated at the proposed parameter vector divided by the posterior evaluated at the current parameter vector:

$$\frac{P(\theta^*_i \mid \theta^s_{-i}, D)}{P(\theta^s_i \mid \theta^s_{-i}, D)} = \frac{P(\theta^*_i, \theta^s_{-i}, D)}{P(\theta^s_i, \theta^s_{-i}, D)}.$$

4. If $i < 8$, set $i = i+1$ and go to step 2. If $i = 8$ and $s < S$, set $s = s+1$, $i = 1$, and go to step 2. If $i = 8$ and $s = S$, the chain is complete.

Conditions for convergence of the Metropolis–Hastings algorithm are very weak. Let Θ be the support of $P(\theta \mid D)$. Then, as long as one begins the chain from some $\theta^0 \in \Theta$ and as long as the proposal density (in our case, the random walk) assigns positive probabilities to transitions from any $\theta^s \in \Theta$ to any $\Theta_1 \subseteq \Theta$ such that $P(\theta \in \Theta_1 \mid D) > 0$, this algorithm generates a serially correlated sequence of θ's that converges to the stationary distribution $P(\theta \mid D)$ (e.g., Geweke (1997)). As a practical matter, acceptance rates between 0.15 and 0.50 tend to generate chains that "mix" well; that is, that move relatively quickly through the support of $P(\theta \mid D)$. Accordingly, we choose the covariance matrices Σ_{ϑ_i} to keep acceptance rates in this range. Also, to ensure that

the chain has reached its stationary distribution, it is necessary to discard a sufficiently large initial "burn-in" period.

Because each evaluation of the likelihood function involves repeated, multidimensional numerical integration and because one complete iteration involves eight evaluations, it is only possible to generate approximately ten complete θ draws per minute for the industry with the most plants (knitting mills). We treat the first 10,000 draws as our burn-in and base our analysis on the 90,000 following draws. Visual inspection of the chains suggests that most parameters mix very well and remain within a stable range, although the sunk cost parameters appear to mix rather slowly. We cannot rule out the possibility that the chain is trapped in the neighborhood of one mode, but several experiments with different starting values all led back to the same support.

SENSITIVITY ANALYSIS OF POSTERIOR DISTRIBUTIONS

The priors we use for the reported results are fairly diffuse. To determine the extent of their influence on our results, we scaled the standard deviations of most prior distributions by a factor of 5 and reestimated. The only priors for which we did not do this were for the variance parameters ($\sigma_{\omega 1}, \sigma_{\omega 2}, \sigma_{\varepsilon 1}, \sigma_{\varepsilon 2}, \sigma_{\xi}$) and the roots of the autoregressive processes ($\lambda_{x1}, \lambda_{x2}, \lambda_{\xi}$). We do not adjust the former because our lognormal densities imply that the original specification was already extremely diffuse (with standard deviations on the order of exp(400)), and we do not adjust the latter because the original specification was diffuse on the stationary support $[-1, 1]$.

Tables SI–SIII juxtapose the results reported in the text with our estimates based on the more diffuse priors. If we had been able to generate sufficiently long MCMC chains, all of the differences between the two sets of results would reflect the associated differences in priors. However, with finite chains, it is inevitable that these differences also reflect some sampling error. Note first that relaxing the priors has virtually no effect on the sunk cost and fixed cost parameters. Similarly, domestic size dummies, exchange rate coefficients, and quartiles of the cross-plant distribution of foreign demand elasticities show little sensitivity to the priors. The only parameters that seem to be sensitive to priors concern the gap between foreign and domestic demand elasticities. When we let these differ by a factor of 5 rather than 1, we estimate this gap to be substantially larger. Given that these are, for our purposes, nuisance parameters, this sensitivity has no bearing on our inferences concerning export volumes or export market participation.

IN-SAMPLE FORECASTING

To assess the in-sample fit of our model, we set all parameters to their posterior means $\bar{\theta}$ and simulate a set of revenue trajectories R_i^f for a hypothetical set of plants. This set begins with the same base-year pattern of export market

TABLE SI

POSTERIOR PARAMETER DISTRIBUTIONS: KNITTED FABRICS (MEANS AND STANDARD DEVIATIONS)

	Posterior	Priors Used	Posterior	More Diffuse Priors
		Profit Function Parameters		
Ψ_0 (intercept)	−12.965 (3.058)	$\Psi_0 \sim \mathrm{N}(0, 500)$	−20.568 (4.470)	$\Psi_0 \sim \mathrm{N}(0, 2{,}500)$
Ψ_{01} (domestic size dummy)	1.362 (0.449)	$\Psi_{01} \sim \mathrm{N}(0, 500)$	1.260 (0.412)	$\Psi_{01} \sim \mathrm{N}(0, 2{,}500)$
Ψ_1 (exchange rate coefficient)	4.047 (0.640)	$\Psi_1 \sim \mathrm{N}(0, 500)$	5.801 (0.943)	$\Psi_1 \sim \mathrm{N}(0, 2{,}500)$
λ_x^1 (root, first AR process)	0.458 (0.258)	$\lambda_x^1 \sim \mathrm{U}(-1, 1)$	0.234 (0.318)	$\lambda_x^1 \sim \mathrm{U}(-1, 1)$
λ_x^2 (root, second AR process)	0.709 (0.103)	$\lambda_x^2 \sim \mathrm{U}(-1, 1)$	0.553 (0.113)	$\lambda_x^2 \sim \mathrm{U}(-1, 1)$
$\sigma_{\omega 1}^2$ (variance, first AR process)	0.469 (0.250)	$\ln(\sigma_{\omega 1}^2) \sim \mathrm{N}(0, 20)$	0.196 (0.133)	$\ln(\sigma_{\omega 1}^2) \sim \mathrm{N}(0, 20)$
$\sigma_{\omega 2}^2$ (variance, second AR process)	0.809 (0.264)	$\ln(\sigma_{\omega 2}^2) \sim \mathrm{N}(0, 20)$	0.951 (0.176)	$\ln(\sigma_{\omega 2}^2) \sim \mathrm{N}(0, 20)$
υ (foreign elasticity premium)	0.950 (0.047)	$\upsilon \sim \mathrm{U}(-1, 1)$	4.205 (0.582)	$\upsilon \sim \mathrm{U}(-5, 5)$
λ_ξ (root, measurement error)	0.935 (0.013)	$\lambda_\xi \sim \mathrm{U}(-1, 1)$	0.956 (0.011)	$\lambda_\xi \sim \mathrm{U}(-1, 1)$
σ_ξ (variance, ξ innovations)	1.312 (0.264)	$\ln(\sigma_\xi) \sim \mathrm{N}(0, 20)$	1.722 (0.434)	$\ln(\sigma_\xi) \sim \mathrm{N}(0, 20)$
		Foreign Demand Elasticities (quintiles only)		
η_{Q1} (elasticity, quintile 1)	10.289 (12.032)	$\ln(\eta - 1) \sim \mathrm{N}(2, 1)$	6.968 (11.702)	$\ln(\eta - 1) \sim \mathrm{N}(0.61, 1.95)$
η_{Q2} (elasticity, quintile 2)	12.314 (8.330)	$\ln(\eta - 1) \sim \mathrm{N}(2, 1)$	10.431 (32.340)	$\ln(\eta - 1) \sim \mathrm{N}(0.61, 1.95)$
η_{Q3} (elasticity, quintile 3)	17.866 (11.089)	$\ln(\eta - 1) \sim \mathrm{N}(2, 1)$	13.909 (41.905)	$\ln(\eta - 1) \sim \mathrm{N}(0.61, 1.95)$
η_{Q4} (elasticity, quintile 4)	37.189 (25.331)	$\ln(\eta - 1) \sim \mathrm{N}(2, 1)$	134.517 (120.242)	$\ln(\eta - 1) \sim \mathrm{N}(0.61, 1.95)$
		Dynamic Discrete Choice Parameters		
γ_{S_1} (sunk cost, size class 1)	61.064 (2.628)	$\mathrm{N}(0, 500)$	56.604 (1.846)	$\mathrm{N}(0, 2500)$
γ_{S_2} (sunk cost, size class 2)	59.484 (2.361)	$\mathrm{N}(0, 500)$	55.367 (3.160)	$\mathrm{N}(0, 2500)$
γ_F (fixed cost)	1.372 (1.340)	$\mathrm{N}(0, 500)$	2.621 (1.134)	$\mathrm{N}(0, 2500)$
$\sigma_{\varepsilon 1}$ (std. error, ε_1)	32.240 (8.382)	$\ln(\sigma_{\varepsilon 1}) \sim \mathrm{N}(0, 20)$	25.233 (5.937)	$\ln(\sigma_{\varepsilon 1}) \sim \mathrm{N}(0, 20)$
$\sigma_{\varepsilon 2}$ (std. error, ε_2)	17.630 (4.737)	$\ln(\sigma_{\varepsilon 2}) \sim \mathrm{N}(0, 20)$	18.887 (3.137)	$\ln(\sigma_{\varepsilon 2}) \sim \mathrm{N}(0, 20)$

TABLE SII

POSTERIOR PARAMETER DISTRIBUTIONS: LEATHER PRODUCTS (MEANS AND STANDARD DEVIATIONS)

	Posterior	Priors Used	Posterior	More Diffuse Priors
		Profit Function Parameters		
Ψ_0 (intercept)	−13.645 (4.505)	$\Psi_0 \sim \mathrm{N}(0, 500)$	−11.150 (5.258)	$\Psi_0 \sim \mathrm{N}(0, 2{,}500)$
Ψ_{01} (domestic size dummy)	1.544 (0.789)	$\Psi_{01} \sim \mathrm{N}(0, 500)$	1.029 (1.053)	$\Psi_{01} \sim \mathrm{N}(0, 2{,}500)$
Ψ_1 (exchange rate coefficient)	4.323 (0.957)	$\Psi_1 \sim \mathrm{N}(0, 500)$	3.988 (1.093)	$\Psi_1 \sim \mathrm{N}(0, 2{,}500)$
λ_x^1 (root, first AR process)	0.787 (0.180)	$\lambda_x^1 \sim \mathrm{U}(-1, 1)$	0.907 (0.066)	$\lambda_x^1 \sim \mathrm{U}(-1, 1)$
λ_x^2 (root, second AR process)	0.952 (0.018)	$\lambda_x^2 \sim \mathrm{U}(-1, 1)$	0.964 (0.016)	$\lambda_x^2 \sim \mathrm{U}(-1, 1)$
$\sigma_{\omega 1}^2$ (variance, first AR process)	0.282 (0.144)	$\ln(\sigma_{\omega 1}^2) \sim \mathrm{N}(0, 20)$	0.390 (0.155)	$\ln(\sigma_{\omega 1}^2) \sim \mathrm{N}(0, 20)$
$\sigma_{\omega 2}^2$ (variance, second AR process)	0.422 (0.146)	$\ln(\sigma_{\omega 1}^2) \sim \mathrm{N}(0, 20)$	0.324 (0.151)	$\ln(\sigma_{\omega 1}^2) \sim \mathrm{N}(0, 20)$
υ (foreign elasticity premium)	−0.016 (0.022)	$\upsilon \sim \mathrm{U}(-1, 1)$	3.232 (0.632)	$\upsilon \sim \mathrm{U}(-5, 5)$
λ_ξ (root, measurement error)	0.336 (0.070)	$\lambda_\xi \sim \mathrm{U}(-1, 1)$	0.942 (0.016)	$\lambda_\xi \sim \mathrm{U}(-1, 1)$
σ_ξ (variance, ξ innovations)	0.011 (0.001)	$\ln(\sigma_\xi) \sim \mathrm{N}(0, 20)$	1.084 (0.280)	$\ln(\sigma_\xi) \sim \mathrm{N}(0, 20)$
		Foreign Demand Elasticities (quintiles only)		
η_{Q1} (elasticity, quintile 1)	8.020 (2.907)	$\ln(\eta - 1) \sim \mathrm{N}(2, 1)$	6.130 (17.223)	$\ln(\eta - 1) \sim \mathrm{N}(0.61, 1.95)$
η_{Q2} (elasticity, quintile 2)	12.282 (13.351)	$\ln(\eta - 1) \sim \mathrm{N}(2, 1)$	10.338 (31.384)	$\ln(\eta - 1) \sim \mathrm{N}(0.61, 1.95)$
η_{Q3} (elasticity, quintile 3)	17.866 (11.089)	$\ln(\eta - 1) \sim \mathrm{N}(2, 1)$	13.553 (28.473)	$\ln(\eta - 1) \sim \mathrm{N}(0.61, 1.95)$
η_{Q4} (elasticity, quintile 4)	37.189 (25.331)	$\ln(\eta - 1) \sim \mathrm{N}(2, 1)$	21.448 (151.485)	$\ln(\eta - 1) \sim \mathrm{N}(0.61, 1.95)$
		Dynamic Discrete Choice Parameters		
γ_{S_1} (sunk cost, size class 1)	63.690 (1.934)	$\mathrm{N}(0, 500)$	64.291 (1.819)	$\mathrm{N}(0, 2500)$
γ_{S_2} (sunk cost, size class 2)	52.615 (4.398)	$\mathrm{N}(0, 500)$	46.666 (2.814)	$\mathrm{N}(0, 2500)$
γ_F (fixed cost)	−0.610 (1.042)	$\mathrm{N}(0, 500)$	−0.456 (0.933)	$\mathrm{N}(0, 2500)$
$\sigma_{\varepsilon 1}$ (std. error, ε_1)	12.854 (6.171)	$\ln(\sigma_{\varepsilon 1}) \sim \mathrm{N}(0, 20)$	19.866 (7.660)	$\ln(\sigma_{\varepsilon 1}) \sim \mathrm{N}(0, 20)$
$\sigma_{\varepsilon 2}$ (std. error, ε_1)	30.627 (7.831)	$\ln(\sigma_{\varepsilon 2}) \sim \mathrm{N}(0, 20)$	22.267 (6.852)	$\ln(\sigma_{\varepsilon 2}) \sim \mathrm{N}(0, 20)$

TABLE SIII

POSTERIOR PARAMETER DISTRIBUTIONS: BASIC CHEMICALS (MEANS AND STANDARD DEVIATIONS)

	Posterior	Priors Used	Posterior	More Diffuse Priors
		Profit Function Parameters		
Ψ_0 (intercept)	1.143 (3.642)	$\Psi_0 \sim \mathrm{N}(0, 500)$	8.872 (3.442)	$\Psi_0 \sim \mathrm{N}(0, 2{,}500)$
Ψ_{01} (domestic size dummy)	1.862 (0.813)	$\Psi_{01} \sim \mathrm{N}(0, 500)$	1.276 (0.900)	$\Psi_{01} \sim \mathrm{N}(0, 2{,}500)$
Ψ_1 (exchange rate coefficient)	0.975 (0.745)	$\Psi_1 \sim \mathrm{N}(0, 500)$	−0.503 (0.787)	$\Psi_1 \sim \mathrm{N}(0, 2{,}500)$
λ_x^1 (root, first AR process)	−0.383 (0.186)	$\lambda_x^1 \sim \mathrm{U}(-1, 1)$	−0.367 (0.216)	$\lambda_x^1 \sim \mathrm{U}(-1, 1)$
λ_x^2 (root, second AR process)	0.951 (0.022)	$\lambda_x^2 \sim \mathrm{U}(-1, 1)$	0.957 (0.022)	$\lambda_x^2 \sim \mathrm{U}(-1, 1)$
$\sigma_{\omega 1}^2$ (variance, first AR process)	0.320 (0.109)	$\ln(\sigma_{\omega 1}^2) \sim \mathrm{N}(0, 20)$	0.320 (0.126)	$\ln(\sigma_{\omega 1}^2) \sim \mathrm{N}(0, 20)$
$\sigma_{\omega 2}^2$ (variance, second AR process)	0.491 (0.137)	$\ln(\sigma_{\omega 2}^2) \sim \mathrm{N}(0, 20)$	0.493 (0.143)	$\ln(\sigma_{\omega 2}^2) \sim \mathrm{N}(0, 20)$
υ (foreign elasticity premium)	0.849 (0.126)	$\upsilon \sim \mathrm{U}(-1, 1)$	3.264 (0.958)	$\upsilon \sim \mathrm{U}(-5, 5)$
λ_ξ (root, measurement error)	0.962 (0.011)	$\lambda_\xi \sim \mathrm{U}(-1, 1)$	0.971 (0.009)	$\lambda_\xi \sim \mathrm{U}(-1, 1)$
σ_ξ (variance, ξ innovations)	1.277 (0.389)	$\ln(\sigma_\xi) \sim \mathrm{N}(0, 20)$	1.717 (0.555)	$\ln(\sigma_\xi) \sim \mathrm{N}(0, 20)$
		Foreign Demand Elasticities (quintiles only)		
η_{Q1} (elasticity, quintile 1)	12.098 (13.881)	$\ln(\eta - 1) \sim \mathrm{N}(2, 1)$	5.872 (9.301)	$\ln(\eta - 1) \sim \mathrm{N}(0.61, 1.95)$
η_{Q2} (elasticity, quintile 2)	12.974 (18.682)	$\ln(\eta - 1) \sim \mathrm{N}(2, 1)$	10.188 (30.807)	$\ln(\eta - 1) \sim \mathrm{N}(0.61, 1.95)$
η_{Q3} (elasticity, quintile 3)	14.139 (13.363)	$\ln(\eta - 1) \sim \mathrm{N}(2, 1)$	12.738 (31.555)	$\ln(\eta - 1) \sim \mathrm{N}(0.61, 1.95)$
η_{Q4} (elasticity, quintile 4)	24.604 (27.253)	$\ln(\eta - 1) \sim \mathrm{N}(2, 1)$	28.432 (70.311)	$\ln(\eta - 1) \sim \mathrm{N}(0.61, 1.95)$
		Dynamic Discrete Choice Parameters		
γ_{S_1} (sunk cost, size class 1)	62.223 (3.345)	$\mathrm{N}(0, 500)$	61.073(2.194)	$\mathrm{N}(0, 2500)$
γ_{S_2} (sunk cost, size class 2)	50.561 (5.043)	$\mathrm{N}(0, 500)$	55.254 (3.134)	$\mathrm{N}(0, 2500)$
γ_F (fixed cost)	1.635 (0.983)	$\mathrm{N}(0, 500)$	1.853 (1.734)	$\mathrm{N}(0, 2500)$
$\sigma_{\varepsilon 1}$ (std. error, ε_1)	7.517 (4.109)	$\ln(\sigma_{\varepsilon 1}) \sim \mathrm{N}(0, 20)$	21.495 (8.431)	$\ln(\sigma_{\varepsilon 1}) \sim \mathrm{N}(0, 20)$
$\sigma_{\varepsilon 2}$ (std. error, ε_2)	32.432 (3.196)	$\ln(\sigma_{\varepsilon 2}) \sim \mathrm{N}(0, 20)$	25.463 (8.431)	$\ln(\sigma_{\varepsilon 2}) \sim \mathrm{N}(0, 20)$

participation and domestic sales volume (small versus large) that we observe in the first year of the data set. Thereafter, it evolves with random draws on the model's exogenous stochastic variables x_{it} and ε_{it}. Each ε_{it} realization is a draw from $N(0, \bar{\Sigma}_\varepsilon)$ and each x_{it+1} realization is a draw from $f_{x|y}(x_{it} \mid y_{it}, z_i, e_t, \bar{\theta})$ simulated forward one year.[2] The simulated $(x_{it}, \varepsilon_{it})$ trajectories are combined with actual exchange rate realizations and substituted into equations (3) and (8), evaluated at $\bar{\theta}$, to impute foreign sales trajectories for each hypothetical plant. The entire simulation process is repeated 300 times per plant and, for each set of simulations, trajectories of export market participation patterns and total export revenues are constructed.

Figures S1 and S2 summarize the model's ability to explain temporal variation in aggregate export volumes and total numbers of exporters. Figure S1 shows that predicted total exports are fairly close to the realized trajectories for all industries, that general tendencies to expand or contract are captured by the model, and that realized trajectories always fall within the 10th and 90th percentile bounds. Similar comments apply to Figure S2, although the model shows some tendency to underpredict the number of exporters in the later sample years.

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GILKS, W. A., S. RICHARDSON, AND D. J. SPEIGELHALTER (1996): *Markov Chain Monte Carlo in Practice.* New York: Chapman and Hall/CRC. [1]

[2]Forecasts based on period 0 draws, simulated forward 10 years, also capture realized trajectories within their 10th and 90th percentile bounds, but these bounds are quite wide for predictions more than 3 years into the future.

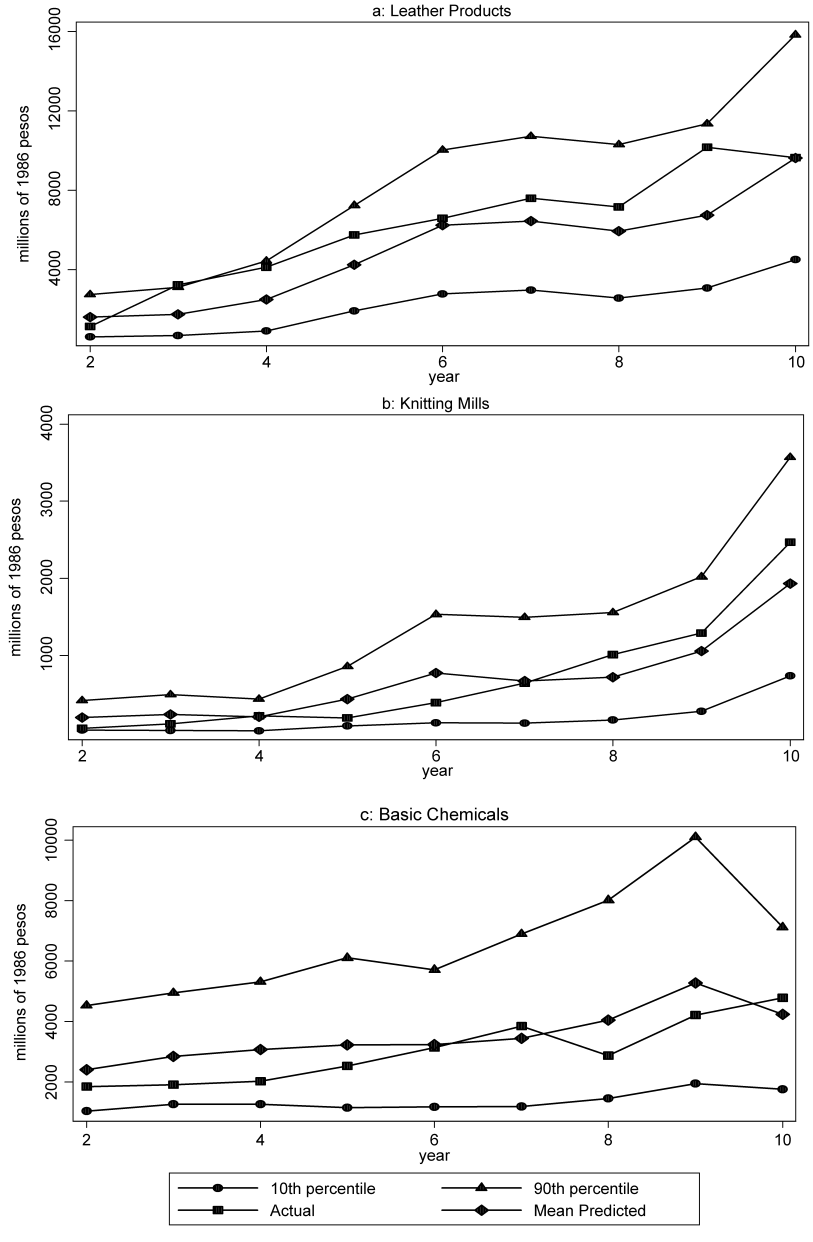

FIGURE S1.—Predicted versus realized total export revenue.

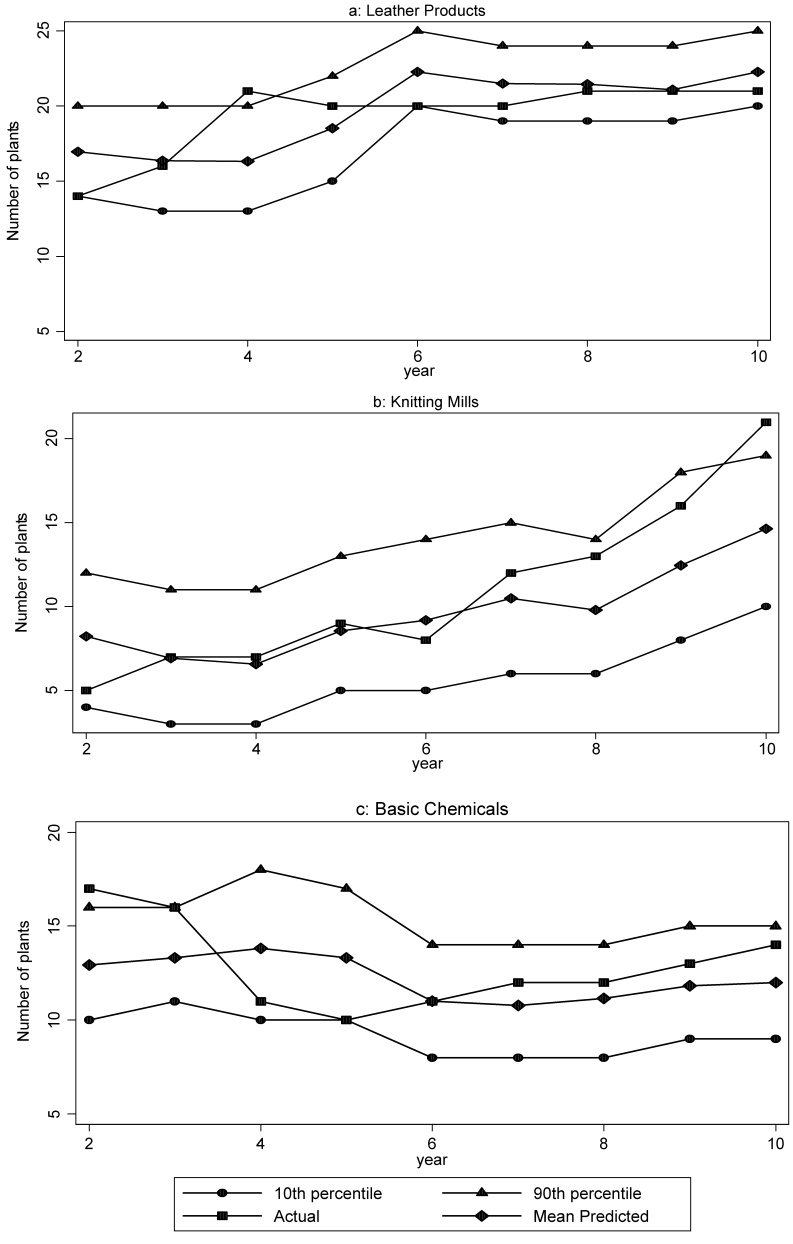

FIGURE S2.—Predicted versus realized total number of exporters.