ADDITIONAL MATERIALS

Product Entry in the Global Automobile Industry

ADDITIONAL MATERIALS A: COUNTERFACTUAL EXERCISES - ROBUSTNESS

I report the effects of the policies studied in Section 7 under two additional points in the confidence set: $(\theta_e, \sigma_e, \theta_g, \sigma_g) = (-4.2, 3.6, -1.8, 2.6)$ (LH) and $(\theta_e, \sigma_e, \theta_g, \sigma_g) = (-4.8, 3.6, -0.6, 2.5)$ (HL). Under the first point, the distribution of market entry fixed costs has a location parameter at the uppermost extreme of the confidence set, while the location parameter of the product portfolio fixed cost is at the lowermost extreme. The opposite is true at point HL. High product portfolio fixed costs and small market entry fixed costs encourage multi-country sales, while low product portfolio and high market entry fixed costs encourage tailoring to local preferences.

A.1. 20% Marginal Cost Subsidy Under Point LH

FIGURE A.1.—Change in Consumer Surplus

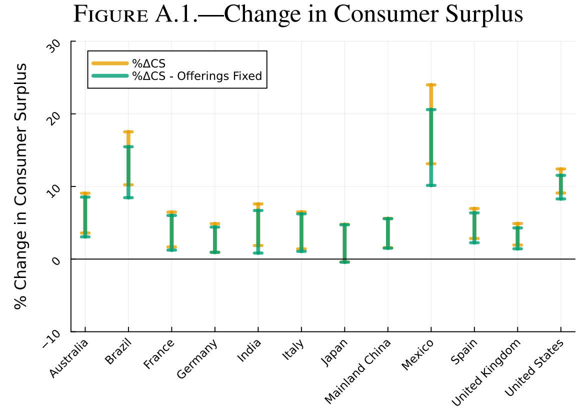


FIGURE A.1.—This figure plots, for each country, bounds on the expected change in consumer surplus (relative to the outside option) following a 20% marginal cost reduction for U.S. brands. The expectation is with respect to bounds on the probability distribution of firms' offerings and demand/marginal cost shocks. The intervals in green show the change in expected consumer surplus using the bounds on the distribution of product offerings before the policy is implemented.

FIGURE A.2.—Number of Products Offered

FIGURE A.2.—Panel A: US Products

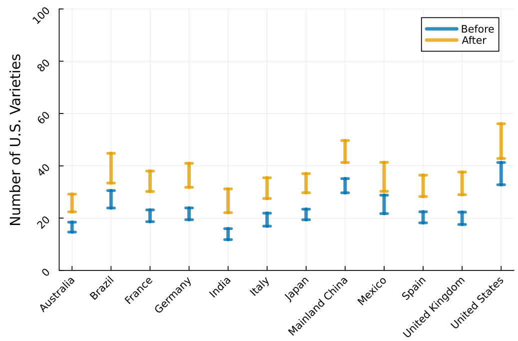


FIGURE A.2.—Panel B: Non-US Products

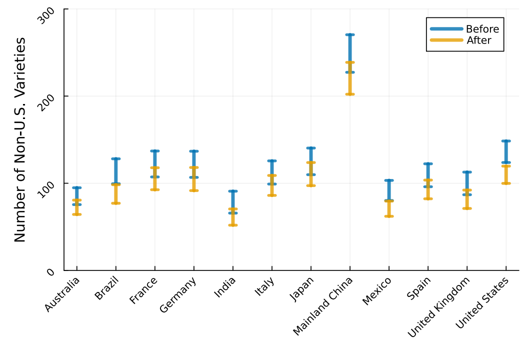


FIGURE A.2.—Panel A displays bounds on the expected number of U.S.-branded products offered across countries before (blue) and after (orange) a 20% reduction in U.S. brands' marginal costs. The expectation is with respect to bounds on the probability distribution of firms' offerings and demand/marginal cost shocks. Panel B displays the corresponding bounds on the expected number of non-U.S.-branded products.

FIGURE A.3.—Market Shares

FIGURE A.3.—Panel A: US Products

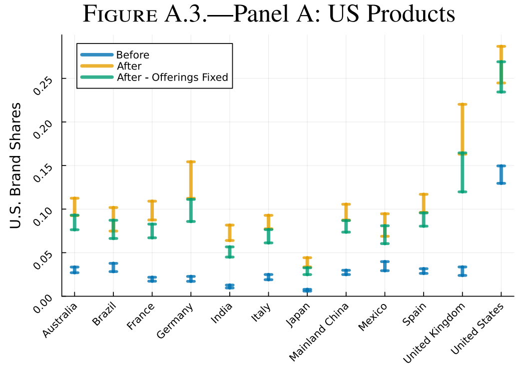


FIGURE A.3.—Panel B: Non-US Products

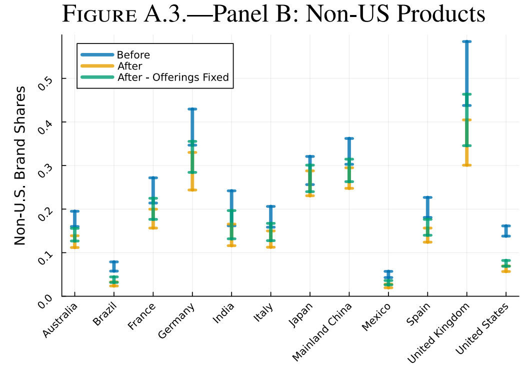


FIGURE A.3.—Panel A displays bounds on the expected total market share of U.S. brands across countries before (blue) and after (orange) a 20% reduction in U.S. brands' marginal costs. The expectation is with respect to bounds on the probability distribution of firms' offerings and demand/marginal cost shocks. The intervals in green use the bounds on the distribution of product offerings in each market before the policy is implemented. Panel B displays the corresponding bounds on the expected total market share of non-U.S. brands before and after the policy.

FIGURE A.4.—Variable Profits

FIGURE A.4.—Panel A: US Products

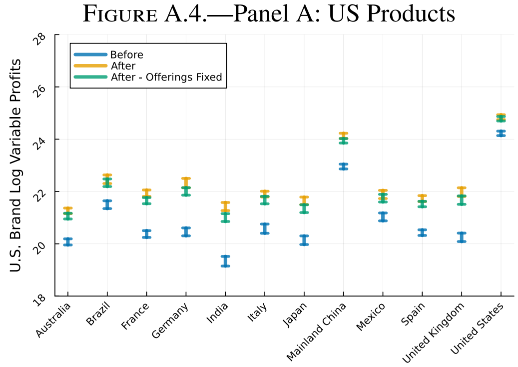


FIGURE A.4.—Panel B: Non-US Products

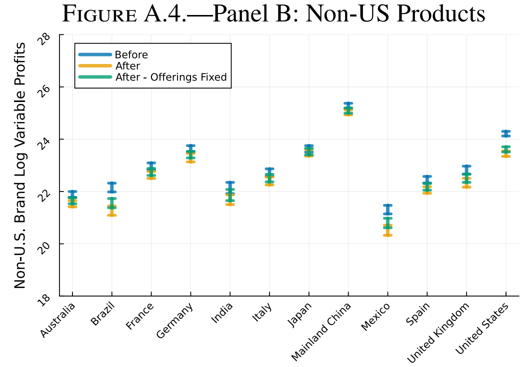


FIGURE A.4.—Panel A displays bounds on the expected (log) total variable profits of U.S. brands across countries before (blue) and after (orange) a 20% reduction in U.S. brands' marginal costs. The expectation is with respect to bounds on the probability distribution of firms' offerings and demand and marginal cost shocks. The intervals in green use the bounds on the distribution of product offerings in each market before the policy is implemented. Panel B displays similar bounds on the expected total market share of non-U.S. brands before and after the policy.

A.2. *20% Marginal Cost Subsidy Under Point HL*

FIGURE A.5.—Change in Consumer Surplus

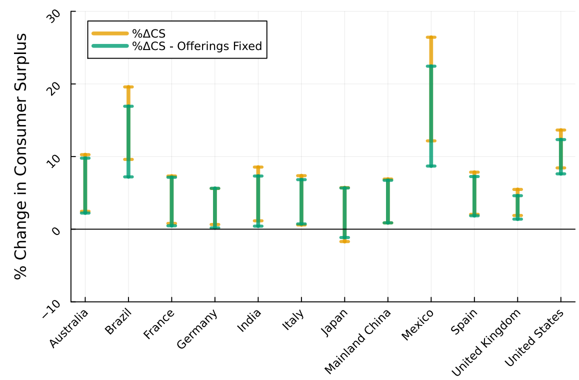


FIGURE A.5.—This figure plots, for each country, bounds on the expected change in consumer surplus (relative to the outside option) following a 20% marginal cost reduction for U.S. brands. The expectation is with respect to bounds on the probability distribution of firms' offerings and demand/marginal cost shocks. The intervals in green show the change in expected consumer surplus using the bounds on the distribution of product offerings before the policy is implemented.

FIGURE A.6.—Number of Products Offered

FIGURE A.6.—Panel A: US Products

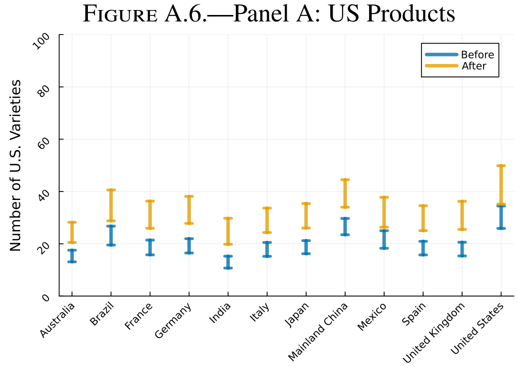


FIGURE A.6.—Panel B: Non-US Products

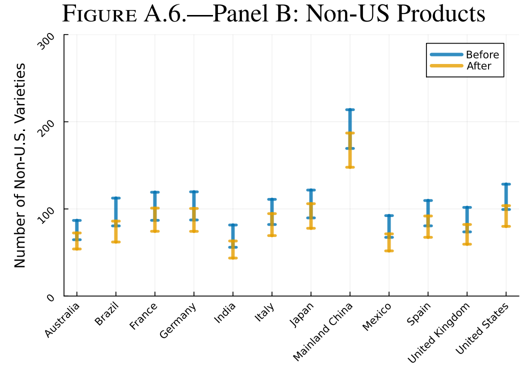


FIGURE A.6.—Panel A displays bounds on the expected number of U.S.-branded products offered across countries before (blue) and after (orange) a 20% reduction in U.S. brands' marginal costs. The expectation is with respect to bounds on the probability distribution of firms' offerings and demand/marginal cost shocks. Panel B displays the corresponding bounds on the expected number of non-U.S.-branded products.

FIGURE A.7.—Market Shares

FIGURE A.7.—Panel A: US Products

FIGURE A.7.—Panel B: Non-US Products

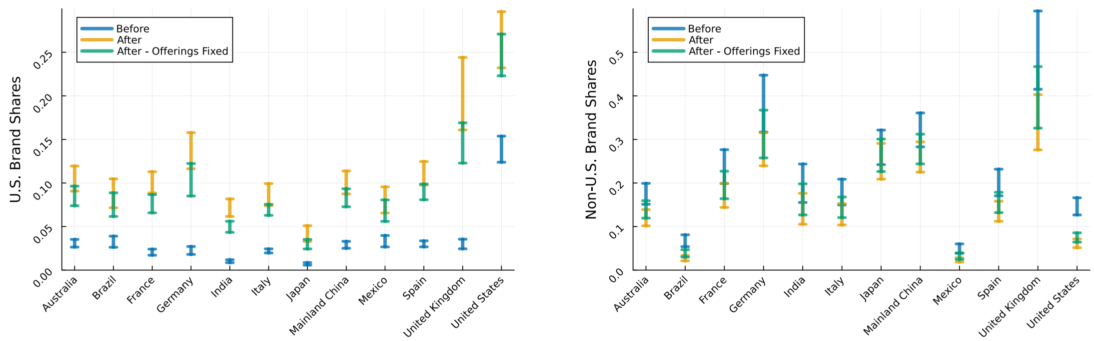


FIGURE A.7.—Panel A displays bounds on the expected total market share of U.S. brands across countries before (blue) and after (orange) a 20% reduction in U.S. brands' marginal costs. The expectation is with respect to bounds on the probability distribution of firms' offerings and demand/marginal cost shocks. The intervals in green use the bounds on the distribution of product offerings in each market before the policy is implemented. Panel B displays the corresponding bounds on the expected total market share of non-U.S. brands before and after the policy.

FIGURE A.8.—Variable Profits

FIGURE A.8.—Panel A: US Products

FIGURE A.8.—Panel B: Non-US Products

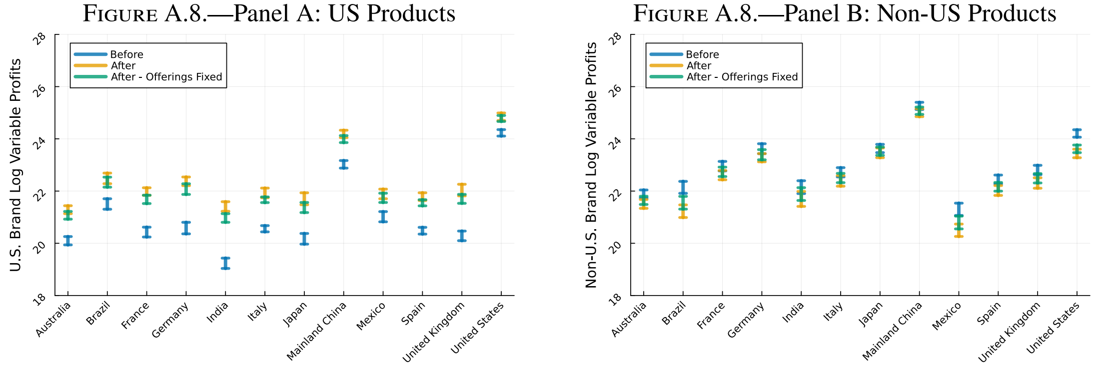


FIGURE A.8.—Panel A displays bounds on the expected (log) total variable profits of U.S. brands across countries before (blue) and after (orange) a 20% reduction in U.S. brands' marginal costs. The expectation is with respect to bounds on the probability distribution of firms' offerings and demand and marginal cost shocks. The intervals in green use the bounds on the distribution of product offerings in each market before the policy is implemented. Panel B displays similar bounds on the expected total market share of non-U.S. brands before and after the policy.

A.3. 50% Consumption Subsidy Under Point LH

FIGURE A.9.—Change in Consumer Surplus

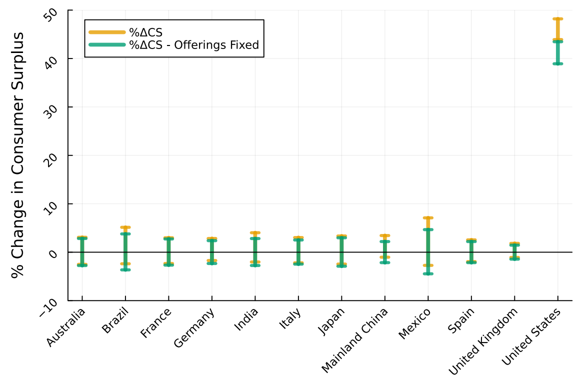


FIGURE A.9.—This figure plots, for each country, bounds on the expected change in consumer surplus following a 50% consumer subsidy for U.S.-branded products in the United States. The expectation is with respect to bounds on the probability distribution of firms' offerings and demand/marginal cost shocks. The intervals in green show the change in expected consumer surplus using the bounds on the distribution of product offerings before the policy is implemented.

FIGURE A.10.—Number of Products Offered

FIGURE A.10.—Panel A: US Products

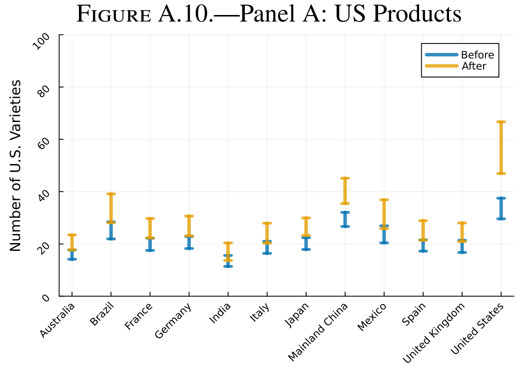


FIGURE A.10.—Panel B: Non-US Products

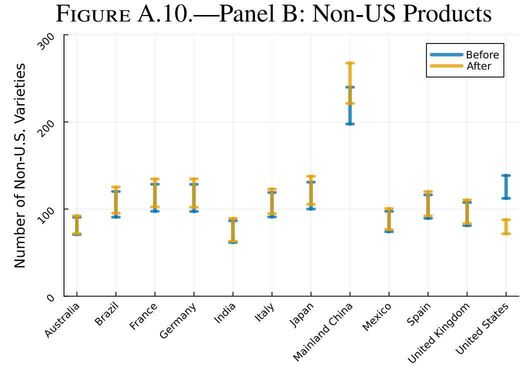


FIGURE A.10.—Panel A displays bounds on the expected number of U.S.-branded products offered across countries before (blue) and after (orange) a 50% consumer subsidy on U.S.-branded products in the United States. The expectation is over bounds on the probability distribution of firms' offerings and demand and marginal cost shocks. Panel B displays the corresponding bounds on the expected number of non-U.S.-branded products before and after the policy.

FIGURE A.11.—Market Shares

FIGURE A.11.—Panel A: US Products   FIGURE A.11.—Panel B: Non-US Products

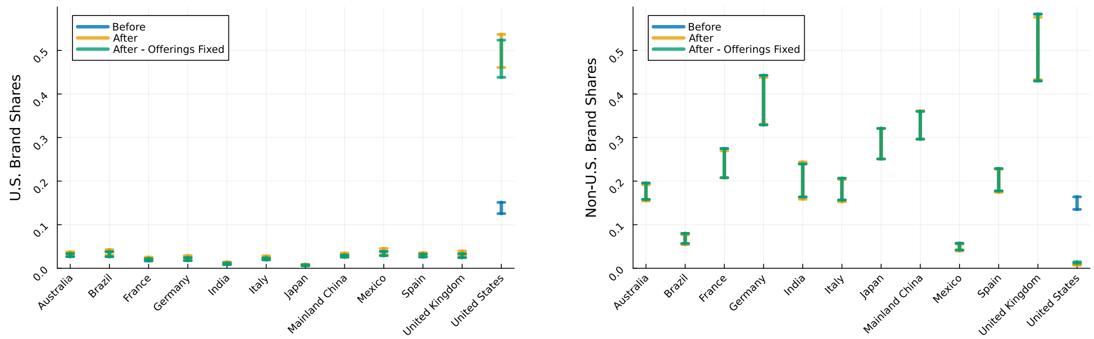


FIGURE A.11.—Panel A displays bounds on the expected total market share of U.S. brands across countries before (blue) and after (orange) a 50% consumer subsidy on U.S.-branded products in the United States. The expectation is with respect to bounds on the probability distribution of firms' offerings and demand and marginal cost shocks. The intervals in green use the bounds on the distribution of product offerings in each market before the policy is implemented. Panel B displays similar bounds on the expected total market share of non-U.S. brands before and after the policy.

FIGURE A.12.—Variable Profits

FIGURE A.12.—Panel A: US Products   FIGURE A.12.—Panel B: Non-US Products

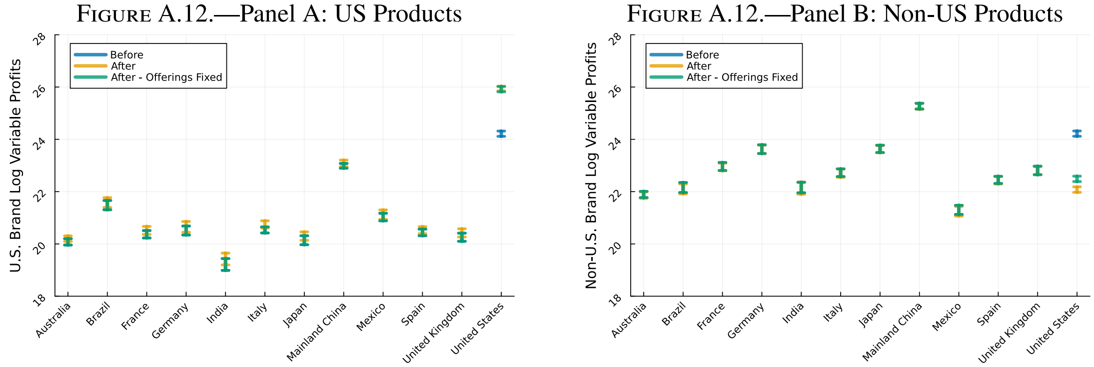


FIGURE A.12.—Panel A displays bounds on the expected (log) total variable profits of U.S. brands across countries before (blue) and after (orange) a 50% consumer subsidy on U.S.-branded products in the United States. The expectation is with respect to bounds on the probability distribution of firms' offerings and demand and marginal cost shocks. The intervals in green use the bounds on the distribution of product offerings in each market before the policy is implemented. Panel B displays similar bounds on the expected total market share of non-U.S. brands before and after the policy.

A.4. 50% Consumption Subsidy Under Point HL

FIGURE A.13.—Change in Consumer Surplus

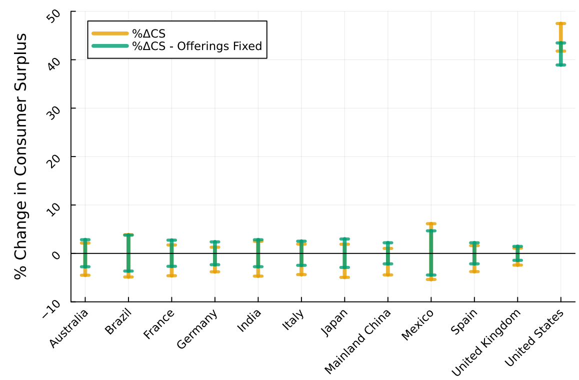


FIGURE A.13.—This figure plots, for each country, bounds on the expected change in consumer surplus following a 50% consumer subsidy for U.S.-branded products in the United States. The expectation is with respect to bounds on the probability distribution of firms' offerings and demand/marginal cost shocks. The intervals in green show the change in expected consumer surplus using the bounds on the distribution of product offerings before the policy is implemented.

FIGURE A.14.—Number of Products Offered

FIGURE A.14.—Panel A: US Products

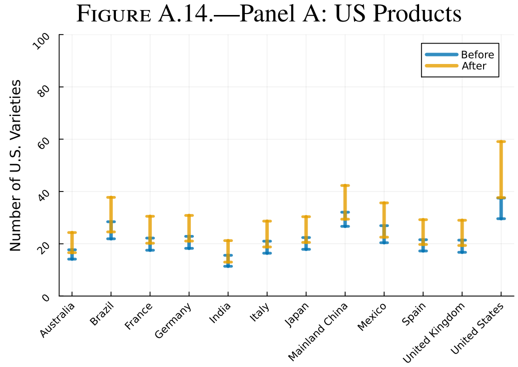


FIGURE A.14.—Panel B: Non-US Products

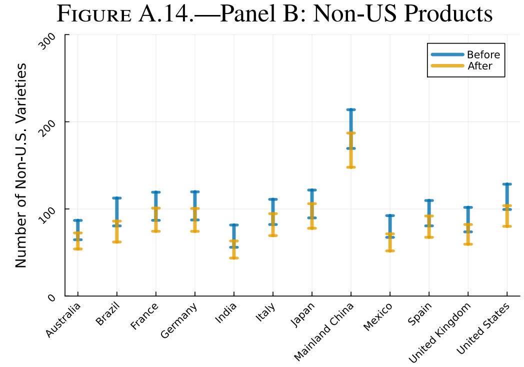


FIGURE A.14.—Panel A displays bounds on the expected number of U.S.-branded products offered across countries before (blue) and after (orange) a 50% consumer subsidy on U.S.-branded products in the United States. The expectation is with respect to bounds on the probability distribution of firms' offerings and demand and marginal cost shocks. Panel B displays the corresponding bounds on the expected number of non-U.S.-branded products before and after the policy.

FIGURE A.15.—Market Shares

FIGURE A.15.—Panel A: US Products

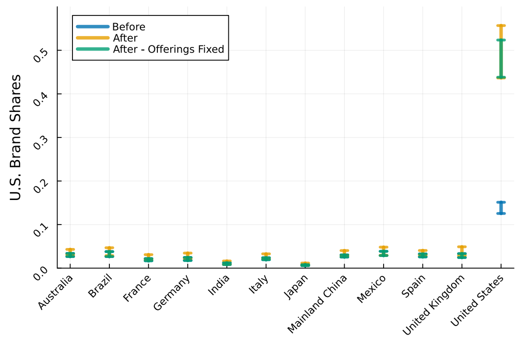


FIGURE A.15.—Panel B: Non-US Products

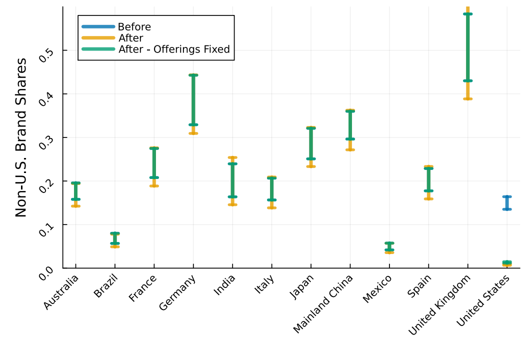


FIGURE A.15.—Panel A displays bounds on the expected total market share of U.S. brands across countries before (blue) and after (orange) a 50% consumer subsidy on U.S.-branded products in the United States. The expectation is with respect to bounds on the probability distribution of firms' offerings and demand and marginal cost shocks. The intervals in green use the bounds on the distribution of product offerings in each market before the policy is implemented. Panel B displays similar bounds on the expected total market share of non-U.S. brands before and after the policy.

FIGURE A.16.—Variable Profits

FIGURE A.16.—Panel A: US Products

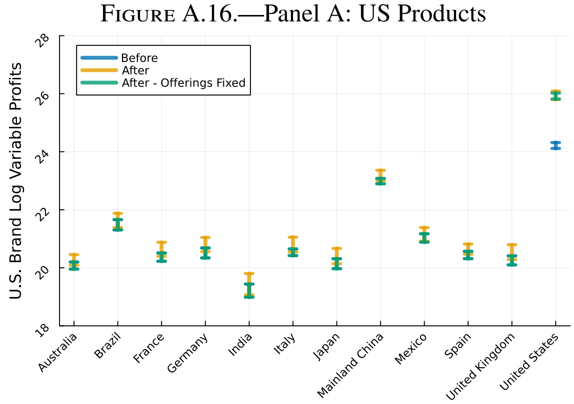


FIGURE A.16.—Panel B: Non-US Products

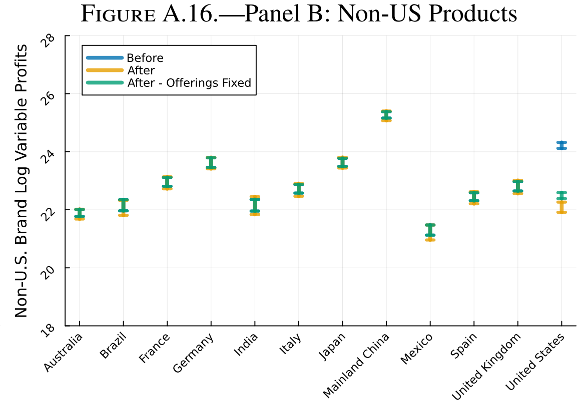


FIGURE A.16.—Panel A displays bounds on the expected (log) total variable profits of U.S. brands across countries before (blue) and after (orange) a 50% consumer subsidy on U.S.-branded products in the United States. The expectation is with respect to bounds on the probability distribution of firms' offerings and demand and marginal cost shocks. The intervals in green use the bounds on the distribution of product offerings in each market before the policy is implemented. Panel B displays similar bounds on the expected total market share of non-U.S. brands before and after the policy.

To prove this result, I use Theorem 3.1 from Balder (1988). This paper provides general existence results for equilibria in Bayesian games. More precisely, the paper shows that provided,

1. The payoff function is measurable on the product set of actions and types,
2. The payoff function is continuous on actions given types,
3. The payoff function is bounded by some $\mathcal{L}_1$ function,
4. The measure of types is absolutely continuous,
5. The action set for each player is a compact set,

then a Nash equilibrium in *behavioral* strategies exists. In my setting, action sets are finite. This trivially implies that condition 5 holds true. Moreover, because any convergent sequence in a finite set is eventually constant, condition 2 also holds. Condition 3 holds because payoffs are bounded below by 0 (firms can always choose to exit all markets and earn 0 profits) and bounded above by the sum (across products $\mathcal{A}^f$) of single-product monopoly profits. In addition, the measure of types is absolutely continuous in my setting due to my assumption of independent and log-normal private types. Finally, the payoff function is measurable on the product set of actions and types. This holds because the payoff function is continuous on own and rivals' actions (since actions are a finite set), own types, and also other firms' types since other firms' types only enter a firm's payoff function through actions. Thus, due to Balder (1988), a Nash equilibrium in behavioral strategies exists.

I now show that I can focus without loss of generality on pure strategy Nash equilibria. To prove this, I use Theorem 4 from Milgrom and Weber (1985). This theorem states that under some conditions, any mixed strategy equilibrium has a "purification", i.e., a pure strategy equilibrium at which each player has the same expected payoff and distribution of observable behavior as at the mixed strategy equilibrium in each of the informational states. The conditions that suffice in my setting are that,

1. Players' types are independent,
2. Players' types are atomless,
3. Each player's payoff depends only on its own type and the list of actions,
4. The action set is finite for each player.

Note that all of these conditions hold in my setting. Therefore, under Assumptions 1-4, there exists a pure strategy Bayesian Nash equilibrium of the global product introduction game.

B.1. Counterexample: No PSNE under Complete Information with More than 2 Players and Strategic Substitutes

Consider the following game:

P3 plays 1

P1/ P2	1	0
1	$(-5,-5,-2)$	$(-4,0,1)$
0	$(0,1,-1)$	$(0,0,2)$

P3 plays 0

P1 / P2	1	0
1	$(1,-1,0)$	$(2,0,0)$
0	$(0,1,0)$	$(0,0,0)$

This is a static binary choice complete information entry game. Each player's payoff from entering is weakly decreasing in the set of entry decisions chosen by other players. No pure strategy Nash equilibrium exists.

ADDITIONAL MATERIALS C: Simulating the Method

In this section, I use simulation to:

1. Test the behavior of the moment inequalities proposed in Section **??** under varying data-generating processes (DGPs),
2. Test the performance of the inference methods used in this paper, based on Andrews and Soares (2010), when a single realization of the product entry game is observed.

To simulate data, I need to solve the model fully. Thus, I simulate a solvable version of my product entry model, which I describe in Section C.1.

C.1. Fully Solvable Version of Global Product Entry Game

The solvable model features N symmetric J-product firms competing in M markets. I set $J = 3$ so that firms have 3 potential products that they can introduce in their global product portfolios and across markets. Both firms and products are symmetric in their profit shifters, but markets are allowed to be heterogeneous.

Profits for firm f from selling N_m^f products in market m take the form,

$$\Pi_m^f(N_m^f, N_m^{-f}) = A_m \frac{N_m^f}{1 + (N_m^f)^{\kappa_o}(N_m^{-f})^{\kappa_r}},$$

where $\kappa_o \in (0,1)$ regulates substitutability across the firm's own products, and $\kappa_r \in (0,1)$ regulates substitution across rival firms' products. A_m is an exogenous market-level profit shifter. Firms draw log-normal fixed costs, as in the main text. I abuse notation and index all firms' potential products as 1, 2, or 3, even though firms draw independent fixed cost shocks.

Timing: The timing is exactly as in the model in the main text. In the first stage, each firm f draws private fixed portfolio cost shocks $\{\nu_j^g\}$ for each of their 3 potential products. Upon observing this private information, firms choose which products to introduce in their portfolio. Next, they draw private fixed market entry shocks $\{\nu_{jm}^e\}_{j \in \mathcal{G}^f, m}$ for each product and choose how many of the products in their portfolio to offer in each market. In the second stage of the game, firms know their portfolio $\mathcal{G}^f$ and must choose which products to offer in each market.

Best response: Firms' best response in Stage 2 depends on portfolio size N_p^f. Let $FE_{mn}^{(k)}$ denote the k^{th} order statistic among the n potential entry cost draws in market m, and let $FD^{(k)}$ denote the k^{th} order statistic among 3 product development cost draws.

If $N_p^f = 1$, the firm sells in market m iff $\mathbb{E}[\Pi_m^f(1, N_m^{-f})|\mathcal{I}] - FE_{m1}^{(1)} \geq 0$.

If $N_p^f = 2$,

$$\begin{cases} 1 \text{ product iff } \mathbb{E}[\Pi_m^f(1, N_m^{-f})|\mathcal{I}] - FE_{m2}^{(1)} \geq 0, \\ \mathbb{E}[\Pi_m^f(2, N_m^{-f})|\mathcal{I}] - \mathbb{E}[\Pi_m^f(1, N_m^{-f})|\mathcal{I}] - FE_{m2}^{(2)} < 0; \\ 2 \text{ products iff } \mathbb{E}[\Pi_m^f(2, N_m^{-f})|\mathcal{I}] - \mathbb{E}[\Pi_m^f(1, N_m^{-f})|\mathcal{I}] - FE_{m2}^{(2)} \geq 0. \end{cases}$$

If $N_p^f = 3$,

$$\begin{cases} 3 \text{ products iff } \mathbb{E}[\Pi_m^f(3, N_m^{-f})|\mathcal{I}] - \mathbb{E}[\Pi_m^f(2, N_m^{-f})|\mathcal{I}] - FE_{m3}^{(3)} \geq 0; \\ 2 \text{ products iff } \mathbb{E}[\Pi_m^f(3, N_m^{-f})|\mathcal{I}] - \mathbb{E}[\Pi_m^f(2, N_m^{-f})|\mathcal{I}] - FE_{m3}^{(3)} < 0, \\ \quad \text{and } \mathbb{E}[\Pi_m^f(2, N_m^{-f})|\mathcal{I}] - \mathbb{E}[\Pi_m^f(1, N_m^{-f})|\mathcal{I}] - FE_{m3}^{(2)} \geq 0; \\ 1 \text{ product iff } \mathbb{E}[\Pi_m^f(2, N_m^{-f})|\mathcal{I}] - \mathbb{E}[\Pi_m^f(1, N_m^{-f})|\mathcal{I}] - FE_{m3}^{(2)} < 0, \\ \quad \text{and } \mathbb{E}[\Pi_m^f(1, N_m^{-f})|\mathcal{I}] - FE_{m3}^{(1)} \geq 0. \end{cases}$$

In Stage 1, define

$$\mathcal{V}_f(N_p^f) = \mathbb{E}\Big[\sum_m \max_{N_m^f \leq N_p^f} \mathbb{E}[\overline{\Pi}_m^f(N_m^f, N_m^{-f})|\mathcal{I}]\Big|\mathcal{I}\Big].$$

The firm develops:

$$\begin{cases} 3 \text{ products iff } \mathcal{V}_f(3) - \mathcal{V}_f(2) - FD_3^{(3)} \geq 0; \\ 2 \text{ products iff } \mathcal{V}_f(3) - \mathcal{V}_f(2) - FD_3^{(3)} < 0, \\ \quad \text{and } \mathcal{V}_f(2) - \mathcal{V}_f(1) - FD_3^{(2)} \geq 0; \\ 1 \text{ product iff } \mathcal{V}_f(2) - \mathcal{V}_f(1) - FD_3^{(2)} < 0, \\ \quad \text{and } \mathcal{V}_f(1) - FD_3^{(1)} \geq 0. \end{cases}$$

The equilibrium solution is summarized by three market thresholds

$$\begin{aligned} t_{1m}^e = \mathbb{E}[\Pi_m^f(1, N_m^{-f})|\mathcal{I}], \quad t_{2m}^e = \mathbb{E}[\Pi_m^f(2, N_m^{-f})|\mathcal{I}] - \mathbb{E}[\Pi_m^f(1, N_m^{-f})|\mathcal{I}] \\ t_{3m}^e = \mathbb{E}[\Pi_m^f(3, N_m^{-f})|\mathcal{I}] - \mathbb{E}[\Pi_m^f(2, N_m^{-f})|\mathcal{I}] \end{aligned} \tag{15}$$

and three product development thresholds,

$$t_1^g = \mathcal{V}_f(1), \quad t_2^g = \mathcal{V}_f(2) - \mathcal{V}_f(1), \quad t_3^g = \mathcal{V}_f(3) - \mathcal{V}_f(2), \tag{16}$$

where $\mathcal{V}_f$ integrates over rival and own product choices, determined by $(t_{1m}^e, t_{2m}^e, t_{3m}^e)$ in equilibrium.

Computing equilibrium profits given threshold strategies: The probability that any firm offers n products, for $n \in \{1,2,3\}$, given the portfolio and market entry strategies, are given by,

$$\begin{aligned}
p_1(\boldsymbol{t}^e,\boldsymbol{t}^g) = {} & \mathbb{P}(FD^{(3)} \le t_3^g)[\mathbb{P}(FE_3^{(1)} \le t_1^e) - \mathbb{P}(FE_3^{(2)} \le t_2^e)] \\
& + [\mathbb{P}(FD^{(2)} \le t_2^g) - \mathbb{P}(FD^{(3)} \le t_3^g)][\mathbb{P}(FE_2^{(2)} \le t_2^e) - \mathbb{P}(FE_2^{(1)} \le t_1^e)] \\
& + [\mathbb{P}(FD^{(1)} \le t_1^g) - \mathbb{P}(FD^{(2)} \le t_2^g)][\mathbb{P}(FE_1^{(1)} \le t_1^e)], \qquad (17)
\end{aligned}$$

$$\begin{aligned}
p_2(\boldsymbol{t}^e,\boldsymbol{t}^g) = {} & \mathbb{P}(FD^{(3)} \le t_3^g)[\mathbb{P}(FE_3^{(2)} \le t_2^e) - \mathbb{P}(FE_3^{(3)} \le t_3^e)] \\
& + [\mathbb{P}(FD^{(2)} \le t_2^g) - \mathbb{P}(FD^{(3)} \le t_3^g)]\mathbb{P}[FE_2^{(2)} \le t_2^e], \qquad (18)
\end{aligned}$$

$$p_3(\boldsymbol{t}^e,\boldsymbol{t}^g) = \mathbb{P}(FD^{(3)} \le t_3^g)\mathbb{P}(FE_3^{(3)} \le t_3^e). \qquad (19)$$

To compute expected profits in the first stage given any N_p^f, first realize that $\mathcal{V}_f$ takes the following form,

$$\mathcal{V}_f(N_p^f) = \sum_m \sum_{i=1}^{N_p^f} \mathbb{P}(N_m^f = i | N_p^f)[\mathbb{E}[\Pi_m^f(i, N_m^{-f})|\mathcal{I}] - i\mathbb{E}[F_{jm}^e | F_{jm}^e \le \mathbb{E}[\Pi_m^f(i, N_m^{-f})|\mathcal{I}]]].$$

Equations (17)-(19) characterize $\mathbb{P}(N_m^f = i|N_p^f)$ as a function of $(\boldsymbol{t}^e,\boldsymbol{t}^p)$. Given expected variable profits, $\mathbb{E}[\Pi_m^f(i, N_m^{-f})|\mathcal{I}]$, the term $\mathbb{E}[F_{jm}^e | F_{jm}^e \le \mathbb{E}[\Pi_m^f(i, N_m^{-f})|\mathcal{I}]]$ is simple to compute numerically using Gaussian quadrature. I use the QuadGK package in Julia to compute this expectation.

To compute $\mathbb{E}[\Pi_m^f(i, N_m^{-f})|\mathcal{I}]$ for each i given $(\boldsymbol{t}^e,\boldsymbol{t}^g)$, I use the DSP package in Julia to perform a convolution which gives the probability distribution of the number of rival product offerings given the number of firms N and $p_n(\boldsymbol{t}^e,\boldsymbol{t}^g)$ for $n \in \{1,2,3\}$.

Solving for $(\boldsymbol{t}^e,\boldsymbol{t}^g)$: Given $(\boldsymbol{t}^e,\boldsymbol{t}^g)$, I showed how to evaluate $\mathcal{V}_f$ and $\mathbb{E}[\Pi_m^f(i, N_m^{-f})|\mathcal{I}]$ for any $i \in \{1,2,3\}$. Thus, I solve for $(\boldsymbol{t}^e,\boldsymbol{t}^g)$ by solving the non-linear system of equations given by equations (15)-(16). To do so, I use the NLsolve Julia package.

C.2. Behavior of Moment Inequalities Across DGPs

In this section, I study how the tightness or informativeness of the moment inequalities varies with parameters κ_o and κ_r and with the number of firms N. Intuitively, the informativeness of the inequalities should depend on the loss from bounding the marginal value of introducing a product by evaluating it at extreme bundles and on the loss from applying Jensen's inequality to average out firms' expectational errors.

Implementation: I simulate $S = 500$ different realizations for each of $T = 12$ different "types" of global product and market entry game described in the previous section. In each game (s, t), there are N firms competing in 12 markets. I hold fixed the market-level profit shifters and set them at $A_m^{(s,t)} = 0.2mt$ for $m \in \{1, 2, ..., 12\}$, $t \in \{1, 2, ..., 12\}$, and $s \in \{1, 2, ..., 500\}$. Different values of t generate variation in profitability across different game types. In this subsection, I perform valid asymptotics as $ST \to \infty$. With $ST = 6000$, simulation noise is small, so I report identified sets, thus ignoring sampling uncertainty (i.e., without computing confidence sets).

True parameters: I set the true parameters to be $(\theta_g, \sigma_g) = (3, 1)$ and $(\theta_e, \sigma_e) = (1, 1)$.

Instruments: For the Stage 2 inequalities (market entry), I condition on the realized set of portfolio decisions and construct instruments following the PPML procedure described in the main text. More precisely, I project the minimal (maximal) marginal values at the product-market level – evaluated at all (no) products in the portfolio being introduced in the market and at the realized set of rival offerings decisions – on a specification of the form $\gamma_0 \exp(\gamma_m^t A_m^{(s,t)})$. I then compute the predicted values of both regressions, sort them, and define 4 percentile categories and bins associated with these categories. This gives 8 instruments in total – 4 for the upper bound inequality and 4 for the lower bound inequality.

For the Stage 1 inequalities, I implement an equivalent procedure as with the Stage 2 inequalities, but without conditioning on the realized product portfolios. I project the realized maximal and minimal (where now the minimal marginal value does not condition on the observed portfolio, so is evaluated at all 3 products being introduced in each market) marginal values on a specification of the form $\gamma_0 \exp(\gamma_m^t A_m^{(s,t)})$. I then compute the predicted values of both regressions and sum them across markets. Then, I sort the sums across markets and define 4 percentile categories for both the lower and the upper bound and define 4 bins associated with these categories, yielding 8 instrument bins - 4 for the lower bound and 4 for the upper bound.

C.2.1. Baseline: $N = 10$, $\kappa_o = 0.1$, $\kappa_r = 0.1$

In this baseline case, I set the number of firms to $N = 10$ and set $\kappa_o = 0.1$ and $\kappa_r = 0.1$. In this case, I obtain the following contour plots and identified sets for (θ_e, σ_e) and (θ_g, σ_g).

FIGURE C.1.—Lower Contours

FIGURE C.1.—θ_g

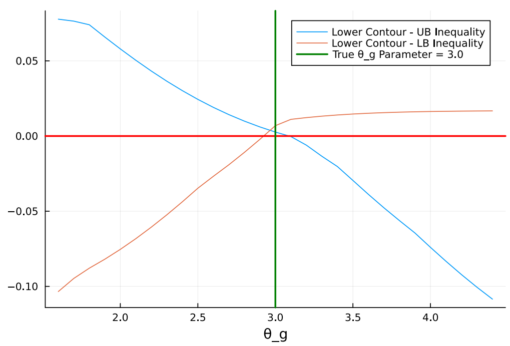


FIGURE C.1.—σ_g

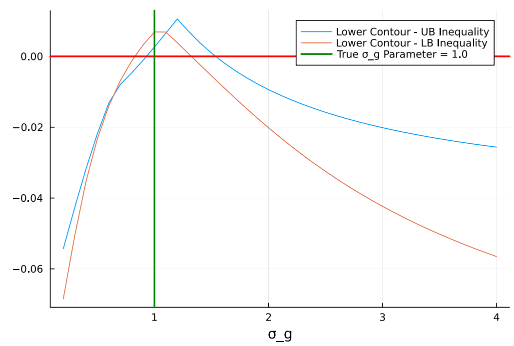


FIGURE C.2.—Lower Contours

FIGURE C.2.—θ_e

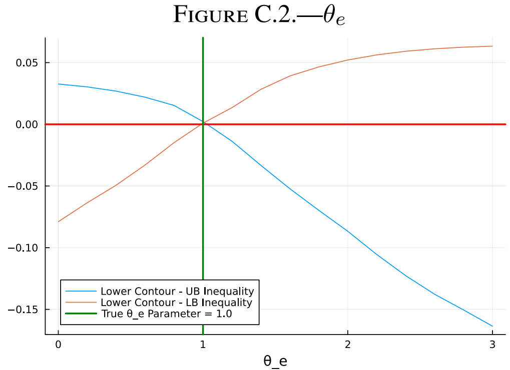


FIGURE C.2.—σ_e

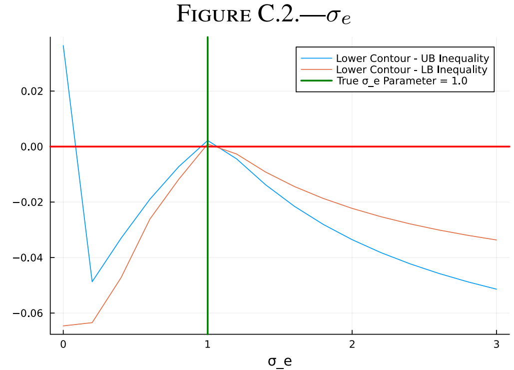


FIGURE C.3.—Identified Sets

FIGURE C.3.—Stage 1

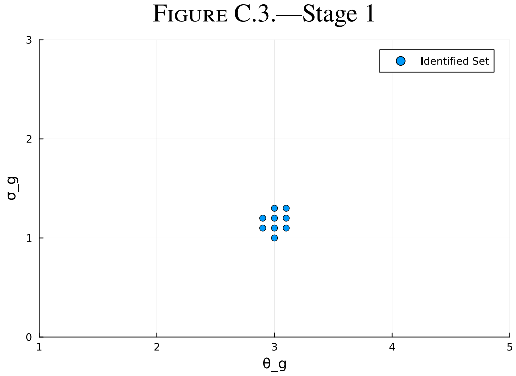


FIGURE C.3.—Stage 2

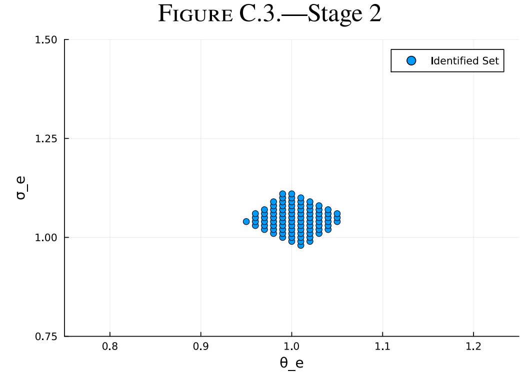


Figure C.1 shows the smallest value that the upper bound and lower bound inequalities take (across each of the 4 instrument bins) as I change the value of θ_g and σ_g, holding the other constant at the true value. The smallest values (or the lower contours) are the most informative because the inequalities are written so that positive values imply acceptance, while negative values imply rejection. For instance, the left panel in Figure C.1 shows that all 4 unconditional lower bound moment inequalities (in orange) and all 4 unconditional upper bound moment inequalities (in blue) are positive conditional on $\sigma_g = 1$ at the region where *both* the orange and blue lines are positive, above the red line indicating that the smallest value of the moments is 0.

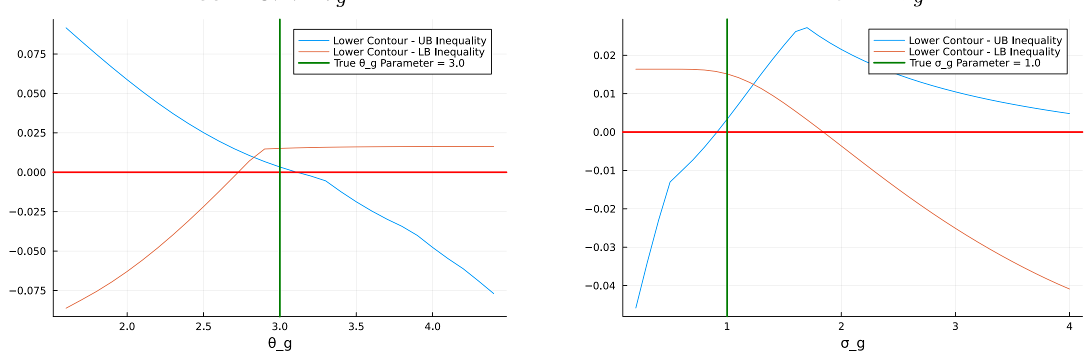
Figure C.3 shows the identified sets for (θ_g, σ_g) and (θ_e, σ_e), which I obtained via grid search. As seen in this figure, the identified set is quite informative both for the Stage 1 and the Stage 2 fixed cost parameters (note: the scale is not the same for the Stage 1 and the Stage 2 parameters).

C.2.2. High Substitutability Within the Firm: $N = 10$, $\kappa_o = 0.25$, $\kappa_r = 0.1$

I now study a deviation from the baseline case in which the parameter determining substitution within the firm is larger, and all else is as in the baseline case.

FIGURE C.4.—Lower Contours

FIGURE C.4.—θ_g FIGURE C.4.—σ_g



Figures C.4-C.6 show the results. Compared to the baseline cases, high substitution within the firm reduces the informativeness of the fixed cost parameter bounds, both for the Stage 1 and for the Stage 2 fixed cost parameters. This is expected given that the loss from bounding the marginal value of introducing a product at extreme bundles (all other products vs. no other products offered) is greater when such products are highly substitutable. That

Figure C.5.—Lower Contours

Figure C.5.—θ_e

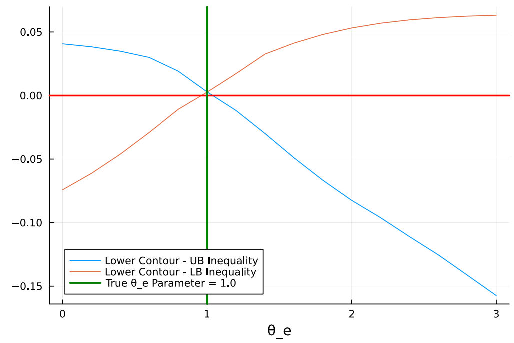


Figure C.5.—σ_e

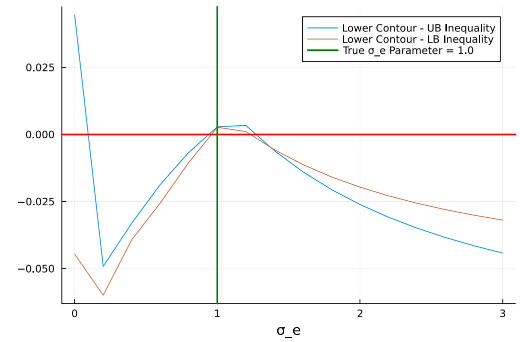


Figure C.6.—Identified Sets

Figure C.6.—Stage 1

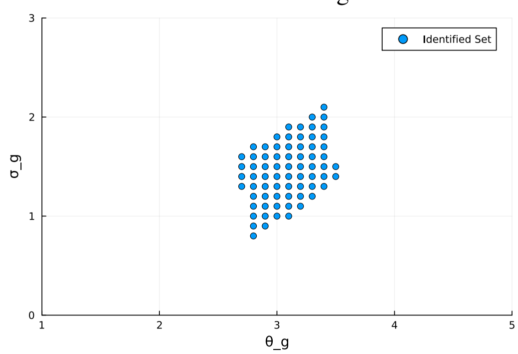
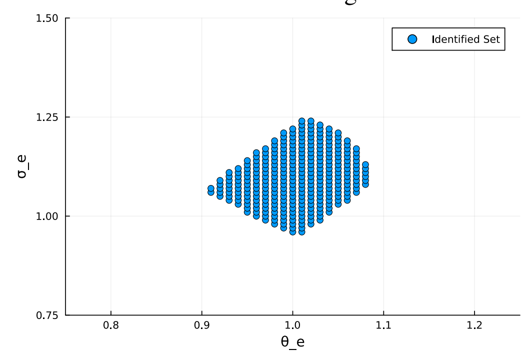


Figure C.6.—Stage 2



is, greater cannibalization within the firm makes the moment inequalities less informative about the true parameters.

C.2.3. Low Substitutability within the Firm: $N = 10$, $\kappa_o = 0.01$, $\kappa_r = 0.1$

Figures C.7-C.9 show what happens when there is very low substitutability across the firms' own products. Interestingly, the tightness of the inequalities increases greatly so that only the true fixed parameters both in Stage 1 and Stage 2 are accepted (given my grid).

This result is of special significance for anyone wanting to use this estimation approach in a setting where firms are single-product (rather than multi-product). Indeed, Figure C.9 shows that in the absence of any interdependence within the firm, my estimation procedure is highly informative, and there is very little to no loss from using my moment inequalities.

FIGURE C.7.—Lower Contours

FIGURE C.7.—θ_g

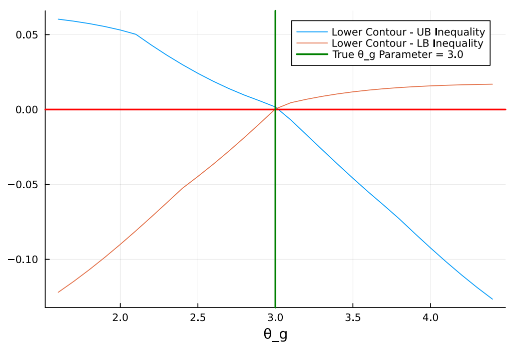


FIGURE C.7.—σ_g

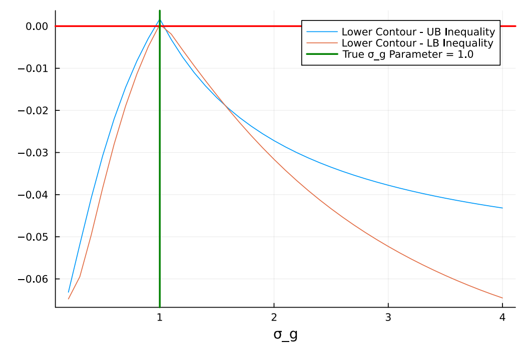


FIGURE C.8.—Lower Contours

FIGURE C.8.—θ_e

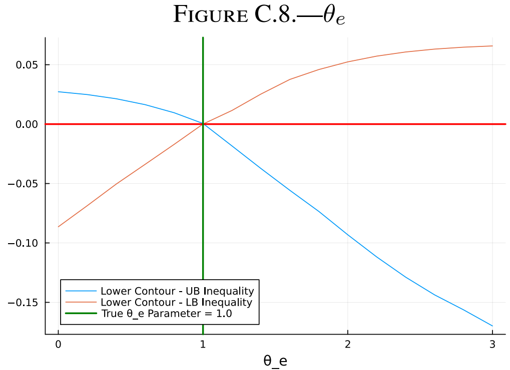


FIGURE C.8.—σ_e

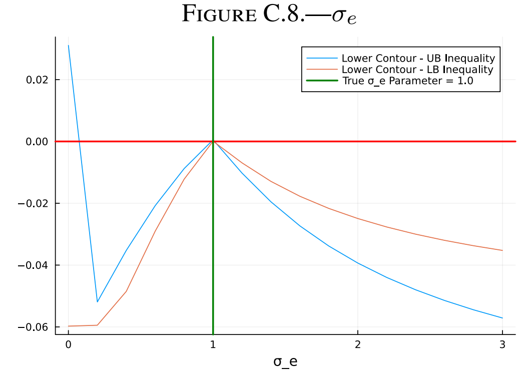


FIGURE C.9.—Identified Sets

FIGURE C.9.—Stage 1

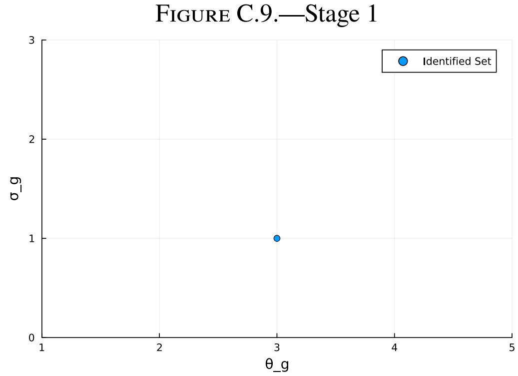


FIGURE C.9.—Stage 2

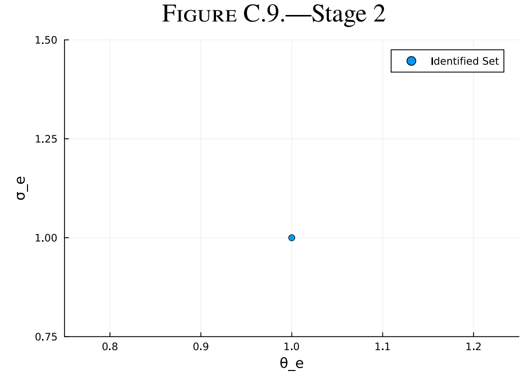


FIGURE C.10.—Lower Contours

FIGURE C.10.—θ_g

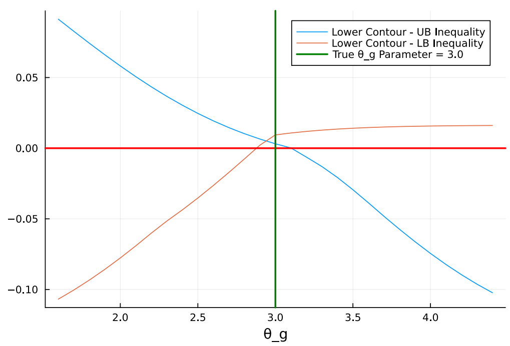


FIGURE C.10.—σ_g

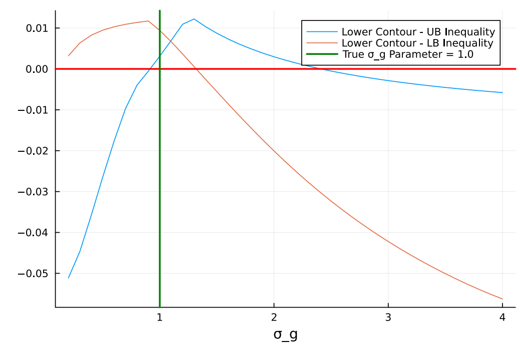


FIGURE C.11.—Lower Contours

FIGURE C.11.—θ_e

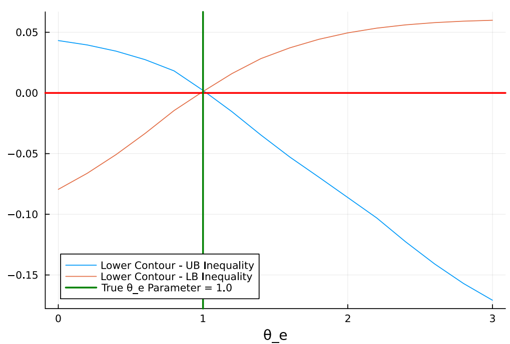


FIGURE C.11.—σ_e

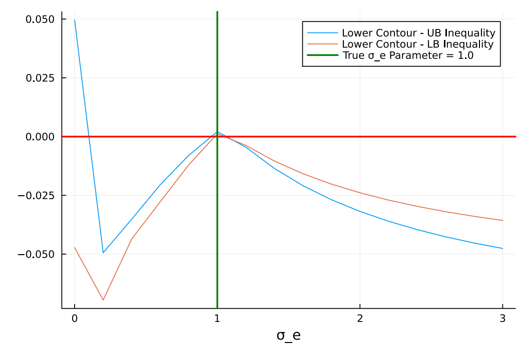
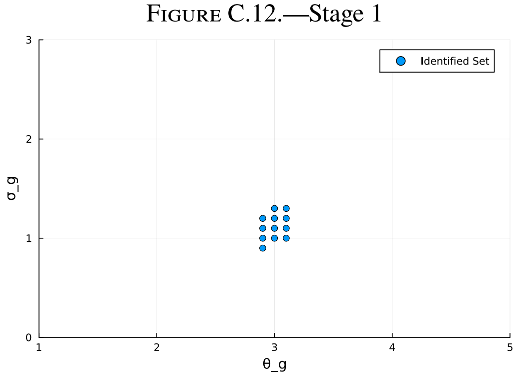
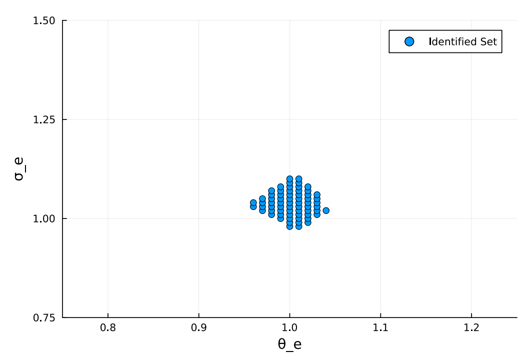


FIGURE C.12.—Identified Sets

FIGURE C.12.—Stage 1





C.2.4. High Substitutability Across Firms: $N = 10$, $\kappa_o = 0.1$, $\kappa_r = 0.25$

Interestingly, high substitution across firms does not seem to change the tightness of the inequalities much relative to the baseline case. While it seems to slightly reduce the informativeness of the Stage 1 inequalities, it does not seem to lead to reduced informativeness in Stage 2. If anything, in this case, the Stage 2 inequalities yield tighter bounds on θ_e. The impact of higher κ_r on the informativeness of the inequalities is therefore not as quantitatively important as the impact of κ_o. This makes sense because, by virtue of the unobservability of rivals' fixed cost shocks, I showed that one can use the realized set of rival offerings decisions to construct the moment inequalities. Greater substitution across firms reduces the rate of product introduction in equilibrium, but firms expect this, and the informativeness of the moment inequalities is not significantly affected.

C.2.5. Low Substitutability Across Firms $N = 10$, $\kappa_o = 0.1$, $\kappa_r = 0.01$

For completeness, I report the identified sets and lower contours for the case in which there is low substitution across rival firms' products. As expected, there are no substantial differences in the informativeness of the moment inequalities relative to the baseline case for the same reasons as in Section C.2.4.

FIGURE C.13.—Lower Contours

FIGURE C.13.—θ_g

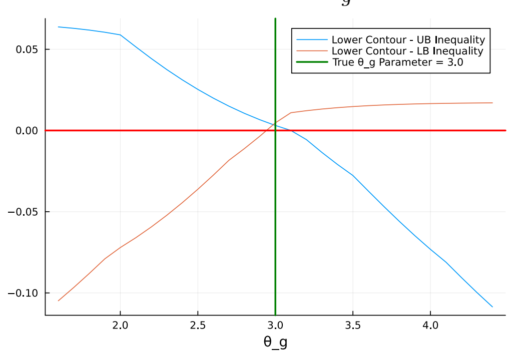
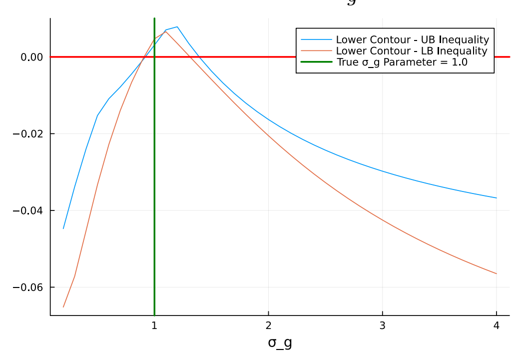


FIGURE C.13.—σ_g



C.2.6. Large Number of Firms: $N = 20$, $\kappa_o = 0.1$, $\kappa_r = 0.1$

Figures C.16-C.18 illustrate the effect of having more firms participating in the global entry game. The identified set becomes slightly smaller when there are more firms. This is due to two effects. First, when there are more firms, each firm makes smaller expectational errors. Second, when there are more firms, more products may be offered on average, which reduces the loss from bounding marginal values with extreme bundles due to submodularity.

FIGURE C.14.—Lower Contours

FIGURE C.14.—θ_e

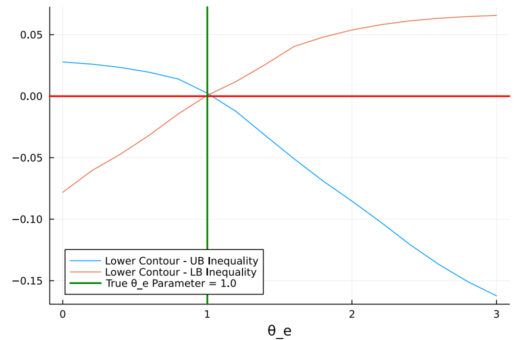


FIGURE C.14.—σ_e

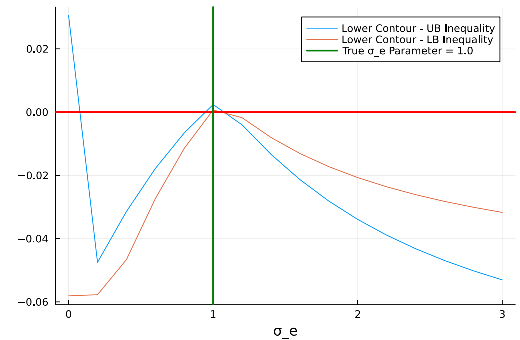


FIGURE C.15.—Identified Sets

FIGURE C.15.—Stage 1

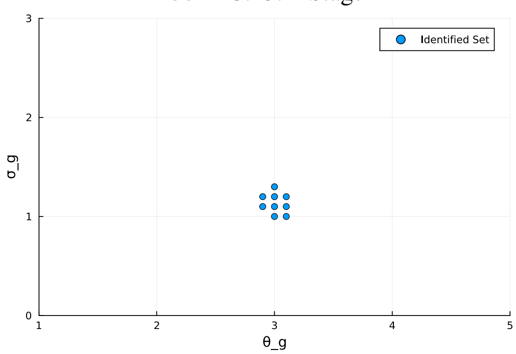


FIGURE C.15.—Stage 2

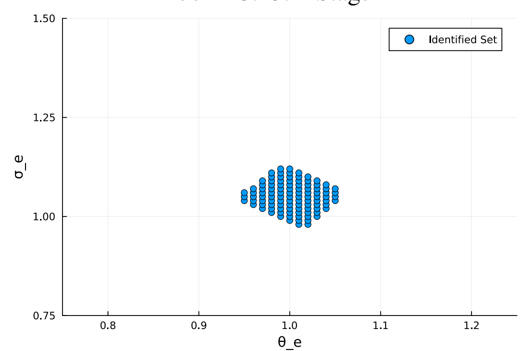


FIGURE C.16.—Lower Contours

FIGURE C.16.—θ_g

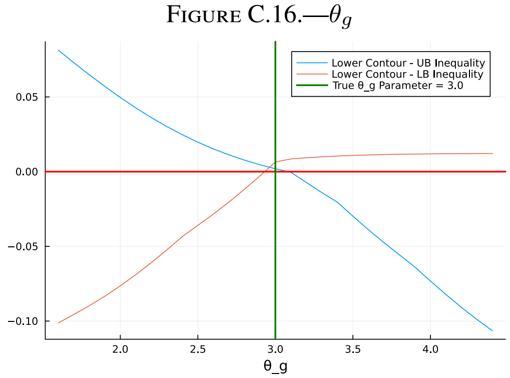
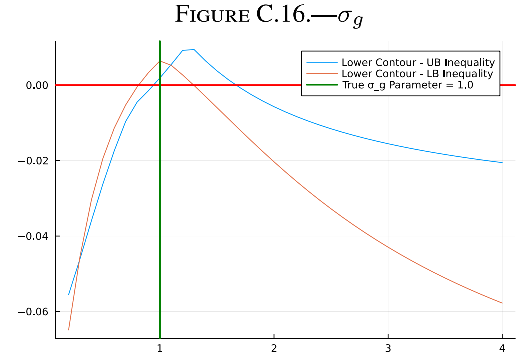


FIGURE C.16.—σ_g



C.2.7. Small Number of Firms: $N = 2$, $\kappa_o = 0.1$, $\kappa_r = 0.1$

Figures C.19-C.21 illustrate the effect of having only 2 firms competing globally. In this case, the inequalities clearly become less informative for the same reasons as argued in Section C.2.6.

C.2.8. Main Takeaways

While the simulations abstract away from heterogeneity across products and across firms, they are still useful for understanding some of the key properties of the moment inequalities. I have established that much of the informativeness of the moment inequalities relies on the extent to which products *within* the firm are substitutable. High degrees of substitutability within the firm render the moment inequalities less informative, while lower degrees of substitutability make them tighter. Moreover, the number of firms (relative to the number of

FIGURE C.17.—Lower Contours

FIGURE C.17.—θ_e FIGURE C.17.—σ_e

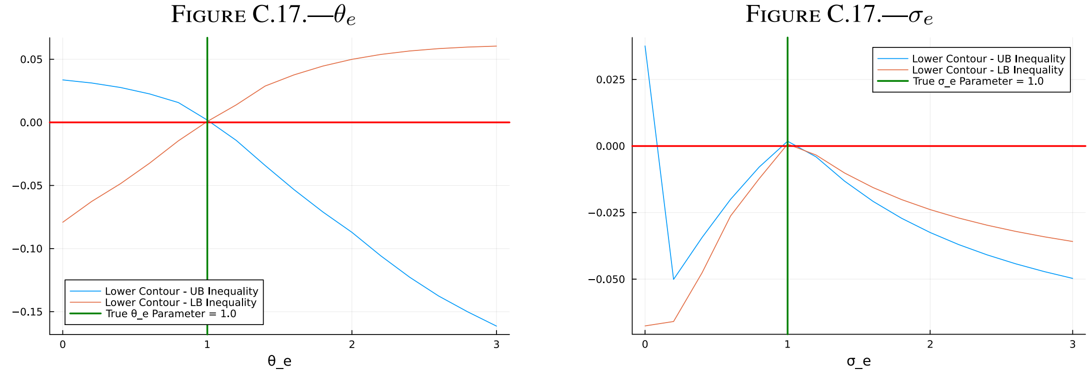


FIGURE C.18.—Identified Sets

FIGURE C.18.—Stage 1 FIGURE C.18.—Stage 2

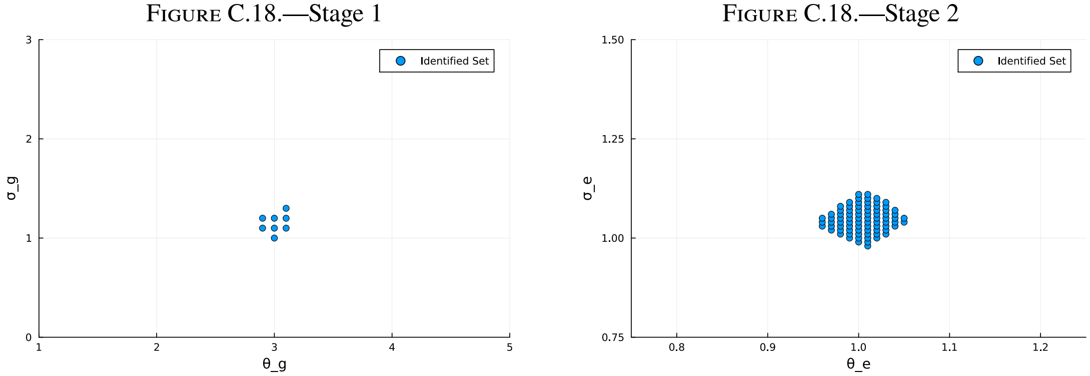


FIGURE C.19.—Lower Contours

FIGURE C.19.—θ_g

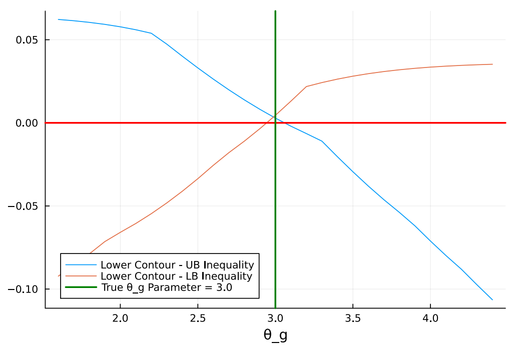


FIGURE C.19.—σ_g

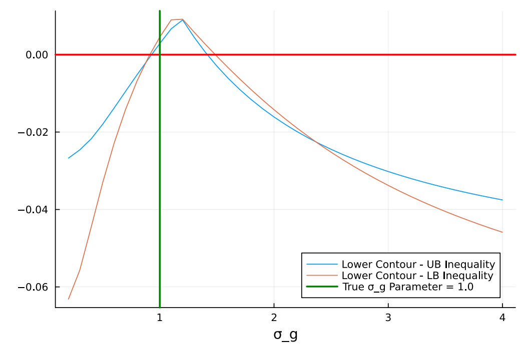


FIGURE C.20.—Lower Contours

FIGURE C.20.—θ_e

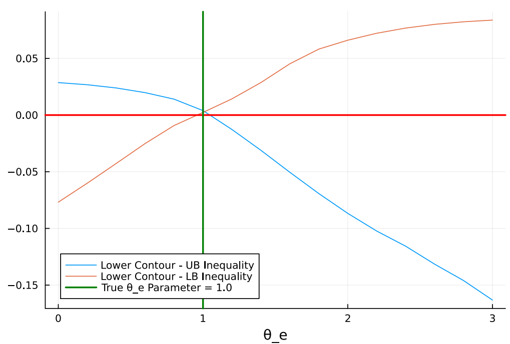


FIGURE C.20.—σ_e

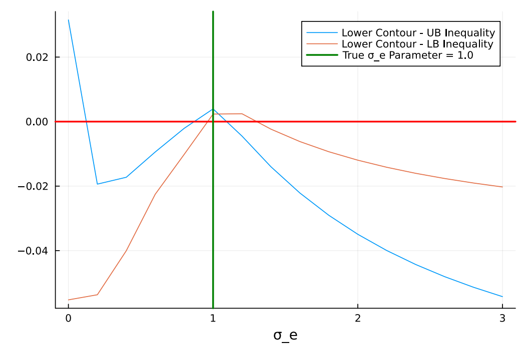


FIGURE C.21.—Identified Sets

FIGURE C.21.—Stage 1

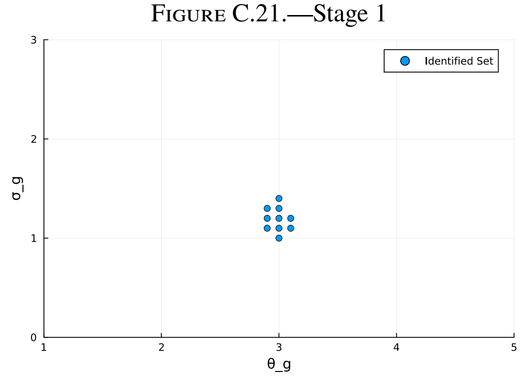
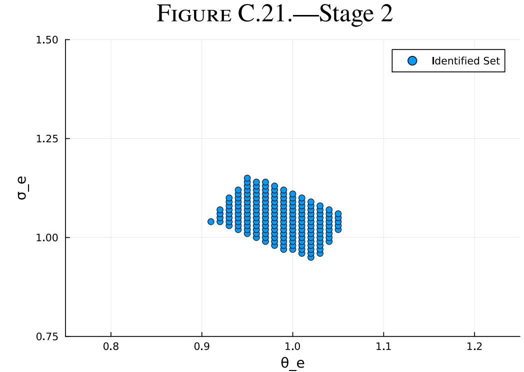


FIGURE C.21.—Stage 2



products per firm) matters. With smaller firms relative to the overall market, expectational errors are smaller. If the set of potential products of a firm is small relative to the set of products that are offered in the market, the loss from bounding a product's marginal value with extreme bundles within the firm is smaller. Finally, I showed that all else equal, substitution across firms does not have much of an effect on the tightness of the moment inequalities.

C.3. Inference Under a Single Realization of Global Product Entry Game

In this section, I use the fully solvable version of the model to assess the properties of Andrews and Soares (2010) confidence sets in my setting. I simulate $S = 100$ realizations for each of $T = 12$ different "types" of global product and market entry games, just as in Section C.2. In each game (s,t), there are N firms competing in 12 markets. I hold fixed the market-level profit shifters and set them at $A_m^{(s,t)} = 0.2mt$ for $m \in \{1, 2, ..., 12\}$, $t \in \{1, 2, ..., 12\}$ and $s \in \{1, 2, ..., 100\}$. Different values of t generate variation in profitability across different game types.

True parameters: I set the true parameters to be $(\theta_g, \sigma_g) = (3, 1)$ and $(\theta_e, \sigma_e) = (1, 1)$.

Instruments: I construct the instruments as described in Section C.2. However, I run the PPML regressions at the (s,t)-level to mimic the actual implementation in the main text, where I only observe a single realization of the cross-section. Thus, the variation used to construct confidence sets in this section is across product-market pairs.

For each (s,t) pair, I construct confidence sets for parameters (θ_e, σ_e) using the procedure in Andrews and Soares (2010). For each of the $S \times T$ 95% confidence sets, I record: (i) whether the true values $(1, 1)$ are included in the confidence set (coverage), (ii) the length of the confidence set along the θ_e dimension (holding $\sigma_e = 1$ at the truth), (iii) the length of the confidence set along the σ_e dimension (holding $\theta_e = 1$ at the truth).

Panel A in Table C.1 reports the average coverage of the confidence set across all $S \times T$ realizations of the global product entry game. I do this both under a robust variance-covariance matrix and a clustered (market-level) variance-covariance matrix. Undercoverage can occur, particularly when the number of firms is relatively small. As the number of firms increases, the coverage of the Andrews and Soares (2010) confidence sets tends to increase. Note that clustering does not necessarily yield higher coverage, though this is the case when the number of firms is large ($N = 75$).

Panel B in Table C.1 reports the median length of the confidence set along each of the dimensions of (θ_e, σ_e), conditional on the confidence set not being empty. The confidence

TABLE C.1

CONFIDENCE SET PROPERTIES FOR (θ_e, σ_e)

SE Type	$N = 5$	$N = 25$	$N = 50$	$N = 75$
Panel A: Coverage of True Parameters (%)				
Robust	92.9	93.8	94.1	93.7
Clustered	92.4	94.1	94.1	95.0
Panel B: Median Length of Confidence Set				
Robust	(0.8, 2.8)	(0.4, 0.9)	(0.2, 0.6)	(0.2, 0.5)
Clustered	(0.9, 4.4)	(0.4, 1.6)	(0.3, 1.1)	(0.3, 0.9)

Note: Panel A reports the average coverage across all $S \times T$ simulations of the confidence sets for (θ_e, σ_e). Panel B reports the median length of these confidence sets along each dimension. The first coordinate corresponds to the θ_e dimension conditional on σ_e being at its true value, and the second to the σ_e dimension conditional on θ_e being at its true value. Confidence sets are computed at the (s, t) level, as in the empirical application.

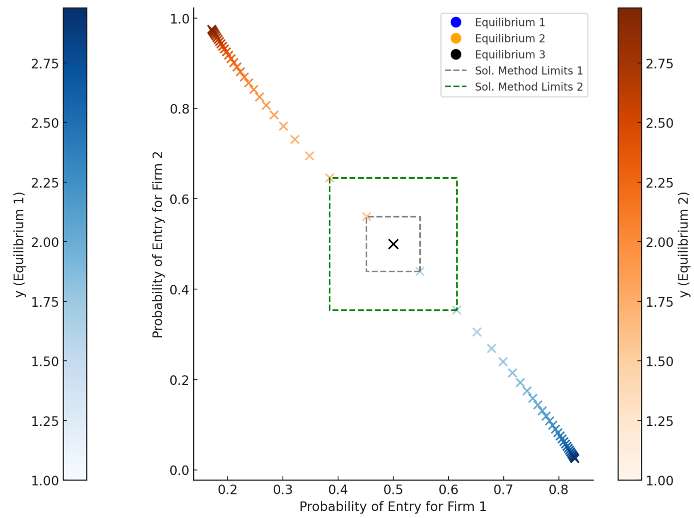
sets are smaller whenever there are more firms and without clustering. In the empirical implementation, I report confidence sets using a robust variance-covariance matrix because (i) Table C.1 (Panel A) shows that clustering does not necessarily improve coverage and undercoverage is not severe, and (ii) Table C.1 (Panel B) shows that clustering leads to a larger confidence set.

A caveat in this exercise is that the simulations require symmetry across firms and products within a (s, t) pair. While at Stage 2, even in the simulations, firms are not fully symmetric due to variation in how many products they have in their global product portfolio, greater symmetry relative to reality should worsen correlation across expectational errors since the realization of the market structure affects firms in (almost) the exact same way. However, greater symmetry also means that there are no "large" firms in the sample. Large firms with a lot of market power can deteriorate the asymptotic properties of the estimator.

ADDITIONAL MATERIALS D: CONVERGENCE OF THE SOLUTION ALGORITHM IN A SIMPLE EXAMPLE

Consider the model with two firms $i = 1, 2$ each making a binary entry decision. Payoffs are:

FIGURE D.1.—Convergence of the Solution Algorithm



P1/ P2	1	0
1	$(-x-\nu_1,-y-\nu_2)$	$(x-\nu_1,0)$
0	$(0,y-\nu_2)$	$(0,0)$

Let $\nu_i \sim Normal(0,1)$ and private information. The one-shot game above has multiple equilibria if and only if $xy > \pi/2$, and the equilibrium in which each firm i enters if and only $\nu_i < 0$ (i enters w.p. 1/2) always exists. I normalize $x = 1$. As y increases, probability of firm 2 entry rises in one equilibrium but declines in another equilibrium. In this very simple example, I apply the solution algorithm from Section 6 to show that the algorithm converges to probabilites of entry $[\underline{p}_i(y), \overline{p}_i(y)]$ for each firm $i = 1, 2$, where $\underline{p}_i(y)$ is the smallest probability of entry for firm i across equilbria under y and $\overline{p}_i(y)$ is the largest probability of entry for firm i across equilibria under y.

Figure D.1 graphically shows this property. The game has three pure strategy equilibria under $y > \pi/2$. The black cross shows that there always exists the equilbrium in which each firm enters with probability $1/2$. In blue, I label Equilibrium 1 as the equilibrium in which firm 1 enters with higher probability; in orange, I label Equilibrium 2 as the equilibrium in which firm 2 enters with higher probability. The green and gray dashed boxes illustrate the convergence points of the solution algorithm at two different values of y. At higher values of y, the difference in the probabilites of entry across equilibria increases. The solution method converges to the dashed “boxes.” It is straightforward to see in this very simple example that the top-right and bottom-left corners of the dashed boxes are not equilibria. Therefore, while the solution method bounds the equilibrium probabilities of entry, it is not necessarily the case that the bounds to which it converges are themselves equilibria.

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