Supplement to "Unobserved heterogeneity in dynamic games: Cannibalization and preemptive entry of hamburger chains in Canada"

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This section reports additional sensitivity analyses. Sections O.1 and O.2 show our estimates based on alternative specifications of the second- and first-stage functional forms. Section O.3 offers additional information on the fit. Section O.4 reports a robustness check of no-preemption counterfactuals with respect to the normalization of exit cost, κ_-.

O.1. More flexible profit function

We specify a standard linear profit function in our main analysis, but one might wonder if such a specification is appropriate when the shape of the estimated policy functions is highly nonmonotonic. To answer this question, Table 12 shows the second-stage estimates with more flexible profit functions in which different values of n_i and n_{-i} enter as dummy variables.

The patterns are consistent with our baseline estimates. The base profit terms, the demographic variables, and the net entry costs do not differ from those in Table 4 (columns 3 and 7) in a statistically significant manner. The flexible competition terms mostly indicate negative effects of competition from the other own- and rival-brand shops, although their statistical significance seems reduced, to the extent that 6 out of the 10 coefficient estimates appear indistinguishable from zero at the conventional levels.

A positive coefficient on $n_{-i} = 2$ in McDonald's profit is intriguing and difficult to interpret in standard entry models. This could be a "spillover" from the nonmonotonic entry CCP estimates and might be symptomatic of a potential tension between the nonmonotonic policy functions and the linear profit functions. Nevertheless, we believe the benefits of the baseline linear specification, such as economically interpretable and statistically significant results, would outweigh those of more flexible ones in Table 12.

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TABLE 12. Second-stage estimates with more flexible profit specification.

	Chain	
	McDonald's	Others
Base profit (α_1)	3.923	1.062
	(0.495)	(1.789)
Type-2 market	−1.007	−0.895
	(0.159)	(0.104)
Type-3 market	−3.779	−1.332
	(0.812)	(0.163)
Own competition (α_2)		
$n_i = 2$	0.395	−1.811
	(0.357)	(2.068)
$n_i = 3$	−2.596	−24.887
	(0.423)	(6.125)
Rival competition (α_3)		
$n_{-i} = 1$	−0.080	−0.138
	(0.135)	(0.484)
$n_{-i} = 2$	0.316	−0.056
	(0.165)	(0.544)
$n_{-i} = 3$	−3.534	−2.056
	(0.369)	(0.404)
Population (θ_1)	0.011	−0.089
	(0.010)	(0.027)
Average income (θ_2)	−0.037	−0.155
	(0.021)	(0.041)
Net entry sunk cost (κ)	34.708	12.935
	(4.772)	(0.367)

Note: This store-level profit function is undefined when $n_i = 0$. The table also excludes $n_i = 1$ and $n_{-i} = 0$, which are omitted categories. Exit cost is normalized to zero, and hence we should interpret κ as the net sunk cost. Standard errors are from bootstrapping across markets.

O.2. PARAMETRIC CCP ESTIMATES WITH MARKET DUMMIES

How far can we go with our preliminary regressions (ordered probit with market dummies)? We prefer nonparametric CCP estimates with a discretized state space as our main analysis, but we could have used a version of parametric CCP estimates if we had not been concerned with potential subtleties in entry/exit incentives. To assess the usefulness of parametric versions of the CCP estimates with market dummies, this subsection runs preliminary regressions with more flexible specifications of market structure (Table 13), which we then use to obtain the estimates of the profit functions (Table 14).

The ordered probit regressions in Table 13 include the squared and interaction terms of N_i and N_j as well as market dummies. We use column 4 as our CCP estimates, instead of the first two steps in our baseline analysis (based on Kasahara and Shimotsu (2009) and Arcidiacono and Miller (2011), respectively), and feed them into Bajari, Benkard, and Levin's (2007) estimation algorithm. The estimates in Table 14 appear counterintu-

TABLE 13. Preliminary regressions (ordered probit) with more flexible market structure.

	Dep. Var.: Decision to Enter/Exit			
	(1)	(2)	(3)	(4)
Own stores	−0.5334***	−0.9689***	−1.1810***	−1.1628***
	(0.0446)	(0.0530)	(0.0543)	(0.0537)
Own stores squared	0.1248***	0.1649***	0.1854***	0.1827***
	(0.0120)	(0.0136)	(0.0138)	(0.0137)
Rival stores	−0.0641***	−0.3281***	−0.2555***	−0.2585***
	(0.0227)	(0.0323)	(0.0332)	(0.0332)
Rival stores squared	−0.0077	0.0134**	0.0066	0.0065
	(0.0055)	(0.0064)	(0.0065)	(0.0065)
Interaction of own & rival stores	−0.0459**	−0.0251	−0.0320	−0.0305
	(0.0187)	(0.0204)	(0.0205)	(0.0205)
Population (thousand, λ_1)	0.0020**	0.0289***	0.0295***	0.0294***
	(0.0010)	(0.0039)	(0.0040)	(0.0040)
Income (thousand C$, λ_2)	0.0022***	0.0171***	0.0182***	0.0182***
	(0.0007)	(0.0021)	(0.0021)	(0.0021)
Market dummies	No	Yes	Yes	Yes
Firm dummies	No	No	Yes	No
McDonald's dummy	No	No	No	Yes
Number of observations	70,000	70,000	70,000	70,000
Pseudo R^2	0.0207	0.0833	0.1240	0.1228

Note: Standard errors are given in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 14. Second-stage estimates based on parametric CCP.

	Chain	
	McDonald's	Others
Base profit (α_1)	−1.789	−1.231
	(18.736)	(28.394)
Own competition (α_2)	5.088	0.013
	(13.330)	(28.535)
Rival competition (α_3)	6.589	2.573
	(2.809)	(1.667)
Population (θ_1)	−3.409	−0.995
	(4.504)	(4.013)
Average income (θ_2)	21.147	3.478
	(3.243)	(3.570)
Net entry sunk cost (κ)	359.703	430.176
	(58.586)	(41.026)

Note: These second-stage estimates are based on column 4 of Table 13 as the first-stage CCP estimates. Standard errors are from bootstrapping across markets.

itive, with positive competition effects (i.e., $\hat{\alpha}_2 > 0$ and $\hat{\alpha}_3 > 0$). We suspect a potential source of biases may reside in the nonmonotonicity of equilibrium entry/exit strategies, as we discussed in the main text.

O.3. Comparison of the CCPs and simulations

As an assessment of the fit, Figure 4 in the main paper plots the evolution of the number of shops in the data and in an MPE of the estimated model. For further investigation, this section compares the CCPs and the simulation patterns between our first- and second-stage estimates.

Figure 9 plots the simulated evolution of McDonald's using the CCP estimates from our first-stage, Arcidiacono–Miller procedure, instead of an equilibrium CCP based on the second-stage estimates of the profit functions. The fit is poor (or nonexistent) in the first half of the sample period but suddenly improves in the second half, and the weighted-average across the three types of markets closely matches the data in the last 10 years.

An immediate cause of this discrepancy between the first and the second halves is that the Arcidiacono–Miller CCP estimates loaded most of the entry actions onto higher demographic states (i.e., states in which z_1 and z_2 are 3 or 4). The exact mechanism behind this phenomenon is unknown, but we speculate that the iterative updating of the type-contingent stochastic objects had some amplifying effects on the different probabilities of entry between relatively "high" and "low" demographic states.

An "opposite" exercise is possible as well. That is, we may investigate the shapes of the model-generated (MPE) strategies in the three-dimensional visual format of Figure 2. In Figure 10, each panel represents an equilibrium CCP of entry by McDonald's in middle-type markets. The left panel exhibits monotonic patterns, whereas the right panel does not.

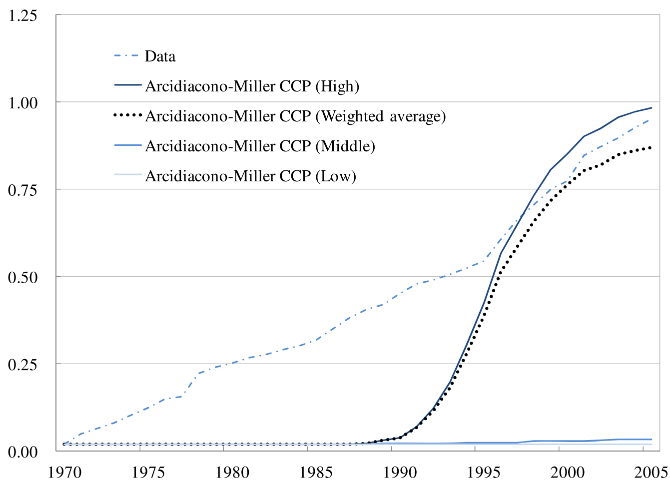

Figure 9. The average number of McDonald's by market type. *Note*: The CCP paths show the mean number of shops across 1000 simulations based on the first-stage CCP estimates.

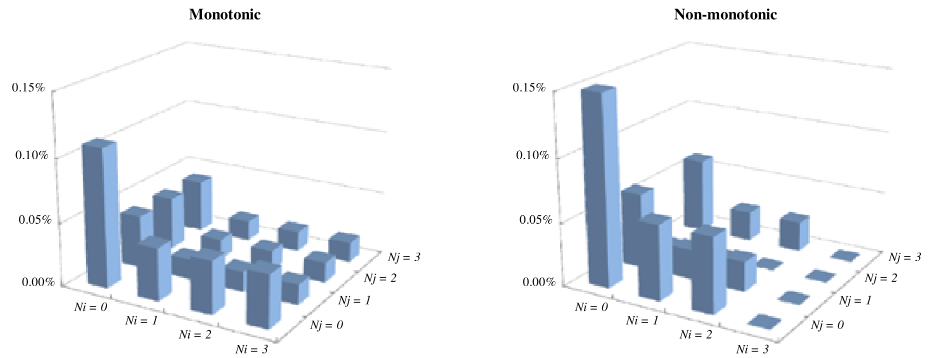

FIGURE 10. Examples of model-generated entry probabilities. *Note*: Each graph represents the CCP estimates of entry by McDonald's in middle-type markets when the market's demography features the highest levels of population (z_1) and income (z_2), and hence they should be compared with the middle-left panel of Figure 2 (with different scaling). The left panel is an example of MPE with monotonic entry strategies, whereas the right panel is that of MPE with nonmonotonic ones.

Our impression from these comparisons is that achieving a perfect fit using a two-step estimation method is an elusive goal in the presence of multiple equilibria. See Section 5.1 for a brief discussion of how we approach this issue practically in the context of a counterfactual simulation.

O.4. NORMALIZATION OF EXIT COST

Our baseline estimates normalize the sunk costs of exit, κ_-, to zero. Figure 11 shows that alternative normalization schemes (i.e., $\kappa_- = 1, 2, 3, 4$, and 5) lead to similar outcomes. This is a subtle but important finding because Judd (1985) showed preemptive investment loses credibility if it is reversible. If setting the exit sunk cost, κ_-, to zero (in our main analysis) is truly a matter of normalization, setting κ_- to different values should not alter our findings with respect to preemption. However, if instead $\kappa_- = 0$ literally eliminated the exit costs, then the resetting of κ_- to positive values would strengthen the effect of preemption, because investment (i.e., entry) should become more irreversible.

Figure 11 exhibits qualitatively similar patterns across panels. The gap between the model (an MPE based on the estimated model) and the no-preemption counterfactual does not seem to vary systematically across different values of κ_-. The gap as of 2005 is 0.30, 0.24, 0.20, 0.20, 0.24, and 0.14 when we set κ_- to 0, 1, 2, 3, 4, and 5, respectively. Moreover, most of the variation in the gap comes from the changes in the model (MPE) paths rather than the counterfactual paths, and hence these differences could be manifestations of multiple MPE. Thus we believe our findings regarding the effect of preemption do not crucially depend on the normalization of κ_-.

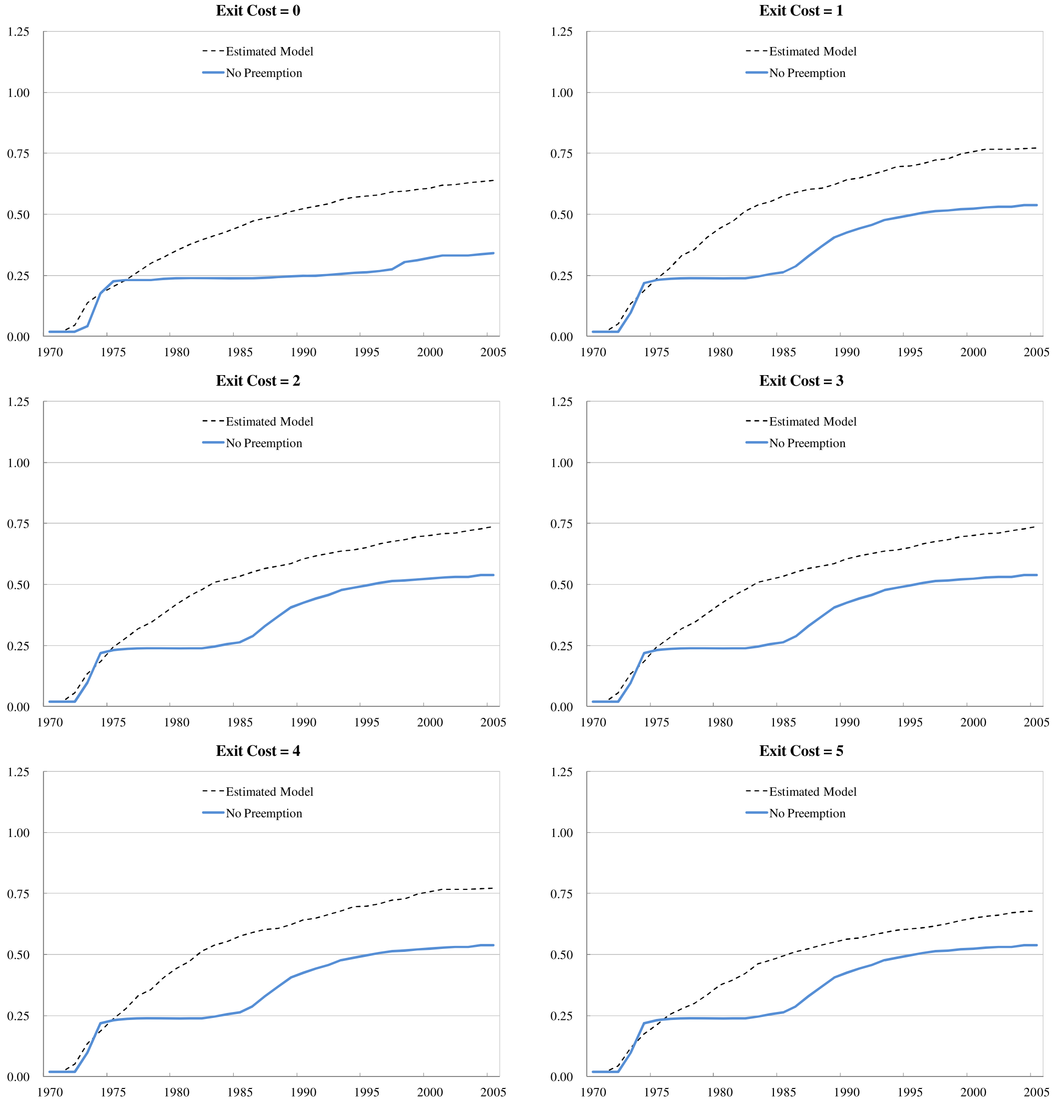

FIGURE 11. Preemption effects and exit-cost normalization. *Note*: The paths show the mean number of McDonald's shops across 1000 simulations (in each of the 400 markets).

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