Web Appendix

to

Public Monopoly and Economic Efficiency: Evidence from the Pennsylvania Liquor Control Board's Entry Decisions

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We estimate a spatial model of liquor demand to analyze the impact of government controlled retailing on entry patterns. In the absence of the Pennsylvania Liquor Control Board, the state would have roughly 2.5 times the current number of stores, higher consumer surplus, and lower payments to liquor store employees. With just over half the number of stores that would maximize welfare, the government system is instead best rationalized as profit maximization with profit sharing. Government operation mitigates, but does not eliminate, free entry's bias against rural consumers. We find only limited evidence of political influence on entry.

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A. Alternative Demand Models

Here, we provide additional detail and present the results of alternative demand specifications that we investigated. Table A-1 below contains estimates for seven demand specifications that employ driving distance as the measure of travel cost.

Specification (1) allows the price coefficient to vary with the log of per-capita income of the tract's black and non-black residents. Specification (2) instead lets the distance coefficient depend on the log of income.

For specification (3), we collected information from ReferenceUSA on the number of grocery stores in the tract, by downloading records for all firms listed in SIC code 541105 and reporting sales of more than $2.5 million, which effectively excludes convenience stores. We interact the number of grocery stores with distance to allow for consumer's increased willingness to travel a given distance to their liquor store if the trip allows multi-stop shopping. In unreported results, we replaced the number of grocery stores with alternative proxies for retail environment, including the tract's number of discounters (Kmart, Target, or Walmart) reported in ReferenceUSA, or the tract's density of retail stores, obtained from Spatial Insights. None of these measures significantly affect demand.

Specification (4) replaces the number of churches per capita with the more narrowly defined number of fundamentalist churches per capita. We rely on Smith (1990) who provides a classification of Protestant denominations into fundamentalist, moderate, liberal, and other. The listing of churches in Pennsylvania that we obtained from ReferenceUSA then allows us to assign each church to one of these four categories based on denomination information contained in the church name, or based on separate "franchise" information reported by ReferenceUSA. Smith (1990) describes fundamentalists as "a movement of conservative or traditionalist Protestant denominations." Our results do not provide evidence, however, that tracts with a higher presence of fundamentalist churches have statistically significantly lower alcohol consumption, even though the point estimate is negative and about twice the equivalent point estimate on church density in general.

Specifications (5) and (6) test for differences between rural and urban counties – by including the county population density – and rural and urban tracts – by including the Census Bureau's classification of tracts into urbanized and rural. We do not find statistically significant differences between rural and urban areas.

Finally, specification (7) investigates how accounting for variation in the presence of potential consumers near a store at different times of the day affects the demand results. We obtain data from the U.S. Department of Transportation Federal Highway Administration's Census Transportation Planning Products (CTPP) on the daytime population of Pennsylvania tracts. Since we focus on the population of legal drinking age, but the CTPP data does not allow classification by age, we uniformly scale down daytime population to sum to the total Pennsylvania population above the age of 21. We then estimate demand from a given tract as the weighted average of the demand of the evening population and of the daytime population, allowing for a separate demand intercept for the tract's daytime population.

Since our data do not contain sales by time of day, a challenge lies in estimating the weight to be placed on the daytime population. Rather than relying on functional form assumptions to potentially pin down the mix of daytime and evening purchases, we obtain data from the U.S. Department of Labor's American Time Use Survey (ATUS) on the share of grocery store trips that occurs during working hours. Using the 2003 through 2010 waves of the ATUS, we keep all grocery shopping activities that occur on non-holiday weekdays during the PLCB's store opening hours of 10 am to 9 pm. We then compute the share of shopping trips that occur before 5 pm and use this as the weight on the daytime population's demand. According to the ATUS data, 58% of grocery store trips occur during working hours.

As in results in Thomadsen (2005), our estimates indicate that the purchase incidence of the daytime population is lower than the purchase incidence of the evening population. The demand elasticity under this specification is −1.6, but the travel cost implied by our estimates is relatively low at 20 cents per km. We investigate in Appendix C how optimal store configurations change under this demand system.

Table A1: Alternative Demand Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
State-bundle list price	-0.4129	-0.1970	-0.2069	-0.2850	-0.1964	-0.1823	-0.2047
	(0.1708)**	(0.1116)*	(0.0618)***	(0.1261)**	(0.0699)***	(0.0406)***	(0.0851)**
State-bundle list price × ln(Income)	0.0750						
	(0.0367)**						
Driving distance	-0.0603	-0.1743	-0.0624	-0.0515	-0.0473	-0.0374	-0.0548
	(0.0183)***	(0.0991)*	(0.0246)**	(0.0182)***	(0.0174)***	(0.0208)*	(0.0111)***
(Driving distance)×(% w/o car)	-0.0032	-0.0052	-0.0059	-0.0064	-0.0065	-0.0064	
	(0.0024)	(0.0023)**	(0.0020)***	(0.0026)**	(0.0022)***	(0.0021)***	
(Driving distance)×ln(Income)		0.0400					
		(0.0315)					
(Driving dist)×I(Grocery store)			0.0160				
			(0.0153)				
Black	0.3265	0.1735	0.2178	0.2993	0.1734	0.1861	0.0183
	(0.2176)	(0.1861)	(0.2186)	(0.1998)	(0.2362)	(0.1946)	(0.0560)
Median Income	0.0084	0.0308	0.0344	0.0350	0.0336	0.0331	0.0426
	(0.0145)	(0.0057)***	(0.0054)***	(0.0039)***	(0.0052)***	(0.0044)***	(0.0051)***
Median Age	0.0015	-0.0003	-0.0009	0.0000	0.0014	-0.0001	0.0094
	(0.0012)	(0.0009)	(0.0006)	(0.0002)	(0.0002)***	(0.0001)	(0.0073)
No churches per capita	-0.0447	-0.0885	-0.1118		-0.0956	-0.0691	-0.2589
	(0.0899)	(0.1064)	(0.1003)		(0.1094)	(0.1085)	(0.0746)***
No fundamentalist churches per capita				-0.1933			
				(0.1717)			
County population density					0.0022		
					(0.0052)		
Urbanized tract						0.0016	
						(0.0012)	
Daytime							-0.3619
							(0.0062)***
Weight, daytime							0.5800
Implied elasticity of demand	-1.5121	-1.5203	-1.5969	-1.8529	-1.5160	-1.4075	-1.5866
Implied travel cost ($) per unit	0.2397	1.2025	0.6065	0.5345	0.6394	0.6260	0.1990

B. Integer Programming Techniques

One of the solution algorithms that we employ uses integer programming techniques in finding several benchmark configurations to compare to the PLCB's current store configuration. In this appendix, we provide a brief overview over the techniques used. We refer the interested reader to Land and Doig (1960) for the initial development of the branch-and-bound method to solve discrete programming problems and Winston (2003) for a more recent, detailed discussion of alternative solution methods. We begin by restating the firm's problem of choosing the optimal set of locations in which to operate stores under the assumption that the firm's objective is to maximize its profit. The benevolent planner's problem of choosing locations to maximize total surplus can be solved analogously.

Consider a market with R possible locations in which consumers reside. Each location is also available as a possible store location. The firm's problem is to decide whether to operate a store in each location s given that each store has total fixed operating costs of K and generates daily variable profit PS_{rst} from serving those consumers in locations $r = 1,\ldots, R$ who choose to frequent a store in location s at time t. We define, for $s = 1,\ldots, R$,

$$\mathrm{y}_s = \begin{cases} 1 & \text{if the firm opens a store in location s} \\ 0 & \text{otherwise} \end{cases} \tag{A.1}$$

Similarly, we define the $R \times R$ assignment matrix Y of consumer location to store matches where Y_{rs} measures the probability of a consumer in location r visiting a store in location s. Our assumption that consumers visit their closest store imply that

$$Y_{rs} = \begin{cases} 1 & \text{if store location } s \text{ is closest to consumer location } r \\ 0 & \text{otherwise} \end{cases} \tag{A.2}$$

The firm's problem consists of choosing a set of store locations y_s, as well as the associated consumer assignment matrix, to maximize total profit. Note that $\mathrm{y}_s = 1$ implies that $Y_{ss} = 1$ and that $y = \mathrm{diag}(Y)$. The assumption that consumers are assigned to their closest store with probability one transforms the store choice problem into what the Operations Research literature denotes a fixed-charge problem that can be formulated as a binary integer program (BIP). We restate the latter from Equations (9) to (12).

The firm chooses y to maximize

$$\max_Y \Pi = \sum_{s=1}^{R}\sum_{r=1}^{R}\sum_{t=1}^{T}\frac{1}{T}PS_{rst}\,Y_{rs} - K\sum_{s=1}^{R}Y_{ss} \quad \text{(A.3)}$$

subject to

$$\sum_{s=1}^{R}Y_{rs} = 1 \quad \forall r, \quad \text{(A.4)}$$

$$Y_{ss} \geq Y_{rs} \quad \forall r,s,r \neq s, \quad \text{(A.5)}$$

$$Y_{rs} = \{0,1\} \quad \forall r,s. \quad \text{(A.6)}$$

The combinatorial optimization literature has suggested several solution approaches to binary integer programming problems. These include (1) complete enumeration; (2) implicit enumeration; (3) rounding of non-integer, linear programming (LP) solutions to the problem, which may result in a solution far from the true solution to the BIP; and (4) a branch-and-bound method combining elements of the enumeration and LP-relaxation approaches; and (4) implicit enumeration using elements of the branch-and-bound method.

Complete enumeration is impractical in our context due to the large number of possible configurations. Implicit enumeration improves upon this procedure by eliminating obviously infeasible solutions using branching diagrams similar to those used in the branch and bound method discussed below, and then evaluating only the remaining solutions to find the optimal one. The remaining configurations to evaluate may still be numerous. We instead employ the branch-and-bound method. Similar to implicit enumeration, not all, but only some - and potentially very few - of the feasible solutions are enumerated; yet, the branch-and-bound method is guaranteed to find the globally optimal solution to the BIP. It proceeds in the following steps:

1. Solve the LP program resulting from replacing the integer constraints for the solution variables in Equation (A.6) with the less stringent requirement of $Y_{rs} \in [0,1] \quad \forall r,s$ using the simplex method. This is commonly referred to as LP-relaxation.

   Since the LP-relaxation is a less constrained version of the original BIP, the feasible solution region for the BIP is contained in the feasible solution region for the corresponding LP-relaxation. As a result, the solution to the relaxed linear programming problem provides a value for the firm's profit that is an upper bound U for the optimal solution to the original BIP. This implies that if the optimal LP answer consists of $\{0,1\}$ integers for all Y_{rs}, then it is also the optimal solution to the constrained BIP.

Notice that the solution of the relaxation allows for fractional allocation of consumers to stores: $Y_{rs} = 1/2$ may be interpreted as allocating half of the consumers in location r to store s.

2. Starting from the solution to the initial LP-relaxation, divide the problem into sub-problems ("branching"). Choose one of the elements of the Y matrix that was assigned a fractional value in the LP solution, $Y_{r's'}$ and subdivide the feasible region of solution values into two sub-problems or nodes, adding, for the chosen Y element, the constraints of $Y_{r's'} = 0$ for sub-problem 1 or $Y_{r's'} = 1$ for sub-problem 2.

   Note also that constraints (A.4) and (A.5) imply that a large number of possible sub-problems are infeasible and can be eliminated ("pruning").

3. Fix the value of $Y_{r's'}$ to the value considered in the sub-problem and find the solution to the resulting LP under the added constraint on $Y_{r's'}$. If the resulting objective function assigned to the sub-problem is worse than an established lower bound L on profit (initially, $L = -\infty$), the entire branch – that is the current sub-problem and any descendants to the sub-problem that could be constructed by adding integer constraints on other partial-value solution elements of Y to the constraint on $Y_{r's'}$ – can be eliminated from further consideration.

4. Partition the sub-problem is again by adding a new Y element to constrain, and investigated. A solution obtained by solving a sub-problem in which all Y elements are integers is a candidate solution. If this candidate solution improves upon the current lower bound to profit, update L.

This process is repeated until no further subdivision is possible, at which point the optimal solution has been reached.

The speed with which a branch-and-bound algorithm finds the solution to a BIP problem depends greatly on finding a close approximation to the solution early, allowing pruning of many sub-problems. This requires a good heuristic for choosing the order of variables to branch on and for selecting the order of nodes to evaluate.

In choosing the sequence of sub-problems to solve, we employ depth-first search with backtracking, where we fully solve one branch of the tree before backtracking to the top of the sub-problem and finding a candidate solution for another branch of the tree. This facilitates re-optimizing the solution to each LP relaxation from the previous one. Further, the branch-and-bound approach requires specification of an order to constructing sub-problems indicating which among the variables Y_{rs} that yield fractional results in the LP-relaxation to branch on first. The Lingo software we employ to solve the store configuration problems selects the order of sub-problems arbitrarily. It further uses various preprocessing steps to detect infeasibilities and possible redundancies among the constraints to improve the lower and upper bounds to the problem.

In problems with large numbers of integer-valued variables and in cases where the LP solution is far from the optimal solution to the BIP, the number of required branching iterations of a branch-and-bound algorithm may be too large for efficient application. For such cases, we employ, as noted in the text, a variant of the "greedy" algorithms discussed in Daskin (1995).

A modeling implication of using linear-programming based techniques is that it is not possible to incorporate a more elaborate store choice model into the optimization process that would recognize the role of other store attributes beyond distance as affecting store choice, such as store size, ease of access, and other unobserved determinants of a store's popularity. LP solution techniques, such as the simplex method we employ, can easily accommodate the fractional assignment matrices for consumer-to-store locations that would result from a probabilistic model of consumer store choice. However, it is not possible in the simplex method to allow the value the solution assigns to one subset of independent variables – in our problem the assignment of consumers to stores Y – to depend on the values of sets of other independent variables to be found as part of the solution. In our problem, incorporating a probabilistic store choice model would imply that the Y matrix depends on the optimal value assigned to every element of the store opening matrix, y.

C. Optimal statewide configurations under alternative demand and fixed costs assumptions

The simulations in Section V rest on a number of inputs. Here, we explore the sensitivity of the results to alternative assumptions.

First, our models assume that fixed costs are the same at all current and possible alternative locations. As discussed in Section I.C, the largest component of store operating costs is labor cost ($5/7^{th}$ of total). Our assumption of constant store operating cost is motivated by the fact that there is no variation across the state in PLCB pay; the PLCB uses a common, state-wide pay scale to compensate its store clerks. The remaining two components to store operating costs are distribution ($1/7^{th}$ of total) and rental expense ($1/7^{th}$). While there may be economies of scale in distribution from serving stores that are clustered together, we have limited information on the PLCB's distribution system and are unable to examine the role of the store configuration in affecting total distribution costs.

We investigate, however, whether allowing for variation in local rental expenses significantly alters the results in Section V.B. We assume that the rental expense contribution to store operating costs is proportional to residential median rent from the 2000 Census and predicted the rental expense at every possible location based on a factor of proportionality derived from summing scaled median rent at the actual store locations to the PLCB's total rental expense. We re-computed the optimal profit and welfare maximizing configurations under this alternative fixed cost measure. The county-by-county exact configurations are very similar in size and welfare to the constant fixed cost configurations. The magnitudes of welfare improvements over actual differ by less than 0.1 percentage points across the two fixed-cost specifications, suggesting that the role played by rental expenses is secondary given its small share in total cost.

Second, our analysis here is entirely static; we predict the optimal configuration using current demand. In practice, long-term leases and other sunk closure costs may introduce adjustments costs to the current network that are reflected in some of the apparent locational inefficiencies we detected in Section V.B. We investigate this by testing whether the PLCB's choice of locations would look more optimal under an earlier demand distribution. We use data from the 1990 Census, together with the demand parameters from specification (1) in Table 3, to predict the optimal county-by-county configurations as of 1990. Regardless of objective, the optimal configurations in 1990 are slightly smaller than their 2000 counterparts, reflecting that real income per-capita has risen over the time period. As in the case of the 2000 configurations, however, the analysis implies significant scope for welfare gains from location adjustments: the optimal 1990 configuration of the same size as the PLCB's store network today entails welfare improvements of 7.2% of revenue relative to the actual configuration, compared to 8.5% when comparing the 2000 configuration to actual. Across Census tracts, the 1990 and 2000 configurations also imply similar deviations in the distance traveled to the closest store from that under the actual configuration. This suggests that sunk closure costs are not a primary explanation for suboptimal location choices.

Third, we investigate the sensitivity of our results to the chosen demand specification. We re-computed welfare under the optimal and actual configurations based on a demand specification that allows for systematic differences in the demand of daytime and evening population (specification (7) in Appendix Table A1) and whose estimates entail an economically low travel cost of only 20 cents per km. While this results in optimal configurations that are between 20 and 35% smaller in size than what we obtain under our main specification, the predicted magnitudes of welfare losses as a share of revenue are similar. As in our current specification, the majority of losses arise from the choice of locations, rather than the size of the network.

D. Regression models investigating political influence

Table A2 presents ordinary least squares models of the number of PLCB stores per house district on characteristics of the house representative and district characteristics. These are discussed in the paper in Section V.D.

Table A2: OLS Models of the Number of PLCB Stores per House District

	(1)	(2)	(3)	(4)
LiquorControlCom	-0.0072		0.2049	
	(0.0569)		(0.0834)**	
LiquorControlCom × Democrat		-0.6226		0.0427
		(0.0498)**		(0.0552)
LiquorControlCom × (1−Democrat)		0.4644		0.2958
		(0.0659)*		(0.0942)**
Democrat	0.8630	0.9835	0.0878	0.0975
	(0.0496)**	(0.0492)**	(0.0489)	(0.0500)
House District Population (000)	0.0083	0.0110		
	(0.0090)	(0.0046)		
Median Family Income (000)	-0.0059	-0.0071		
	(0.0017)	(0.0014)*		
Percent Black	-2.4946	-2.4962		
	(0.0249)**	(0.0039)**		
Percent Hispanic	-2.9363	-2.8528		
	(0.0252)**	(0.1862)**		
Constant	2.6620	2.4845	1.7528	1.8402
	(0.6154)*	(0.3417)*	(0.1074)**	(0.0739)**
Observations	1,015	1,015	1,015	1,015
R-squared	0.15	0.17	0.99	0.99
District FE	No	No	Yes	Yes

Notes: Dependent variable is the number of PLCB stores in the House district. All regressions include year dummies and are clustered on the legislative session. LiquorControlCom equals one if the district's representative serves on the state's liquor control committee. Democrat equals one if the district's representative is a Democrat.

Standard errors in parentheses.* significant at 5% level; ** significant at 1% level.

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