The Welfare Consequences of ATM Surcharges: Evidence from a Structural Entry Model

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Abstract:

Over the past 20 years, automatic teller machines (ATMs) have become a ubiquitous component of consumer banking. Despite their vast presence, ATM prices have risen substantially over the last several years. The rise in prices together with the inherent geographic product differentiation for ATMs imply that the current market structure may not be optimal. For instance, the market may reflect excess entry, where the sum of total consumer and producer surplus would be higher with less ATMs and lower prices. The purpose of this study is to estimate a structural model of the market for ATMs using data on consumer locations and actual and potential ATM locations and to investigate the welfare consequences of ATM price regulations using this model. We model consumers as making a discrete choice of ATMs given a utility function that depends on price and distance, and potential ATMs as choosing entry and price in a simultaneous Bayesian-Nash equilibrium. We estimate the parameters of this model using data from the Minnesota-Iowa border. We develop a simulation-based likelihood estimator that is identified by the quasi-experimental variation created by the fact that Iowa fixed the price of ATMs during our sample period while Minnesota did not.

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1. Introduction

The goal of this paper is to estimate a structural model of the market for automatic teller machines (ATMs) in order to understand the implications of regulating ATM surcharges on ATM entry and consumer welfare. We develop new econometric methods that allow us to feasibly estimate the parameters of a structural equilibrium model using entry data. This paper can help shed light on the theoretically ambiguous implications of free entry on consumer and producer welfare for differentiated products industries in general and ATMs in particular.

Over the last 20 years, ATMs have become a ubiquitous component of consumer banking technology. Studies show that by 2001, there were more than 324,000 ATMs in the United States, with an average of 117 transactions per day per ATM, suggesting that each person in the United States uses an ATM on average 45 times per year, a figure that is still growing.[1]

In spite of the growing and vast presence of ATMs, the market for ATMs may not reflect perfect competition or optimal outcomes, because of product differentiation. In particular, the average price of using an ATM, often called the "surcharge," has increased significantly over the last several years. The increase can be linked to an April, 1996 decision by the major ATM networks to allow surcharges among their member ATMs. Because of the increase in numbers of ATMs, the number of transactions per ATM has fallen by about 45 percent since 1996. The technology of ATMs is characterized by high fixed costs—primarily the cost of purchasing the machine, keeping it stocked with cash, and servicing it—and very low marginal costs. For this reason, the increased price of ATM services has been accompanied by an increased average cost per ATM transaction.

The fact that the average price of ATMs has risen suggests that there may have been "excess" entry of ATMs, in the sense that consumer welfare could have been higher if there had been less entry. It also suggests that a policy by an ATM network or government that regulated or eliminated surcharges could potentially increase total welfare. This would be likely to be true if the entry of new ATMs resulted in significant business stealing from existing ATMs and if the new ATMs did not sufficiently add to consumer welfare. While it is certainly possible that the elimination of the surcharge ban lowered consumer welfare, it is not at all certain. ATMs are differentiated products, with a primary characteristic being their location. The increase in the number of ATMs means that consumers have to travel less distance to use an ATM. This decrease in distance can compensate for the increase in price. Because of the differentiated products nature of the industry, it is theoretically ambiguous whether price restrictions would increase or decrease consumer welfare, with the answer depending on the consumer utility function, the cost structure and the nature of the interactions between the agents in the economy.

For this study, we develop a differentiated products model of ATM demand and costs, where consumer utility is affected by distance and price, and firms face a fixed cost per ATM that can vary by location, but no marginal costs. We create a data set that provides detailed locations for actual and potential ATMs and consumers for the border counties of Iowa and Minnesota. We use the data set together with new econometric techniques to estimate the structural parameters of the model. We then use our estimated parameters to understand the equilibrium implications of a surcharge ban and other policies.

In general, it might be difficult to separately identify the effects of distance and price elasticities using only entry data. However, we are able to identify and estimate these parameters

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by using the fact that the State of Iowa banned ATM surcharges during our sample period.[2] The fact that Iowa did not allow surcharges but its neighboring states allowed them creates a source of local quasi-experimental variation, whereby the different pattern of ATM penetration rates between places in Iowa near its borders and places just outside the borders of Iowa will identify the parameters.[3] We implement this identification idea by first estimating the distance elasticity and cost function using the Iowa data. As price was essentially fixed in that state, any variation in usage does not reflect a difference in prices. We then recover the price elasticity from Minnesota data. For the Minnesota estimation, we use the estimated values for Iowa for all the parameters besides the price elasticity.

Our model of ATM competition for Iowa is as follows. We assume that each entrepreneur at an appropriate retail establishment chooses whether or not to set up an ATM machine. We do not model dynamics or multi-product firms, since the sunk costs of ATMs are low, and the number of potential entrepreneurs is large. Upon entry, the potential ATM will earn a fixed interchange fee per ATM transaction but must pay a fixed cost of operation. The fixed cost includes a common local component and an idiosyncratic component that is i.i.d. across potential ATMs. The idiosyncratic component is observable only to the entrepreneur, and not to other potential ATMs or to the econometrician. The unobservable nature of the cost shock gives rise to a Bayesian-Nash equilibrium, wherein each entrepreneur perceives an independent probability of entry for each other ATM, and makes its entry decision based on its cost shock and this perceived distribution. The entrepreneur chooses to enter when the expected profit from entering at the location is positive. Following the entry process, each consumer makes a discrete

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[2] The surcharge ban was overturned by the U.S. Court of Appeals for the Eighth Circuit in 2002.
[3] Other studies that have identified economic parameters based on the local quasi-experimental variation created by state-level policy differences include Card and Krueger (1994), Fox (1986) and Holmes (1998).

choice among the actual ATMs and no ATM, based on distance and her idiosyncratic terms, but not based on price.

Our model of competition for Minnesota extends the Iowa model to allow for price setting. Firms simultaneously decide whether to enter and, conditional on entry, decide on price. Because the idiosyncratic location term only affects fixed costs, the equilibrium price conditional on entry will not vary based on this term. In Minnesota, following the entry process, each consumer makes a discrete choice among the actual ATMs and no ATM based on distance, price and her idiosyncratic terms.

This study builds on an entry literature started by Bresnahan and Reiss (1991) and Berry (1992). Like more recent papers in this literature (Chernew, Gowrisankaran and Fendrick (2001), Mazzeo (2002) and Seim (2002)) we incorporate detailed geographic and product data that allows us to obtain more realistic results. Two other literatures also bear on this work. Recent studies have sought to understand the theoretical implications of ATM surcharges and to quantify the reasons for surcharging (see Croft and Spencer (2003), Hannan, Kiser, McAndrews and Prager (2002) and Massoud and Bernhardt (2002). In addition, other studies have estimated spatial models in order to understand the prevalence of excess entry (see Davis (2002) and Berry and Waldfogel (1999)).

Our paper is most similar to Seim (2002)'s work in that we model and match the specific location of entry behavior within a localized area and assume incomplete information within the market in order to make estimation of this model computationally feasible. A model of localized competition is crucial for understanding the welfare impact of ATM surcharges, because of the tradeoff between location and price. Our model and estimation strategy differs from and extends Seim's methodology in three important ways. First, we model entry as an explicit function of

fundamental utility and cost parameters and then we use these parameters to evaluate well-defined policy experiments. In contrast, it is not possible to obtain fundamental utility parameters from Seim's work. Second, we use and extend new econometric methods based on Aguirregabiria and Mira (2002)[4] that vastly reduce the computational burden of estimating our model by allowing us to estimate the parameters without solving for the equilibrium of the game. Third, as noted above, we use the source of quasi-experimental variation created by the policy differences between Iowa and Minnesota.

To understand our estimation method, note that a potential way of estimating our model would be to use maximum likelihood. We could evaluate the likelihood for a parameter vector by solving for the Bayesian-Nash equilibrium entry probability for each potential entrant conditional on the parameter vector, and then finding the equilibrium probabilities of the actual entry decisions. Instead, our method uses the fact that, in our model, the equilibrium entry probability for a firm in Iowa, as perceived by the firm's competitors, is a function solely of observable data.[5]

We implement our method by first solving for the equilibrium entry probability of each firm using a reduced-form estimation based on exogenous consumer and potential entrant variables. For the Iowa data, we then simulate the likelihood of a given firm's entry decision by directly substituting the other firms' entry probabilities from the data. This substitution is appropriate since we assume that the data is generated from the model. Its value is that it results in an estimation algorithm that is faster by orders of magnitude then standard maximum likelihood, because it does not require solving for the equilibrium of the model conditional on

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[4] See also Hotz and Miller (1993) and Berry and Pakes (2003).
[5] Guerre, Perrigne and Vuong (2000) use this same insight in a different context to develop a computationally tractable estimator for common value auction games.

parameters. For the Minnesota model, we substitute the entry probabilities from the data, but solve for the price vector in equilibrium, since we cannot evaluate the equilibrium density of price, as we lack price data.

The remainder of this paper is divided as follows. Section 2 describes the model and estimation method. Section 3 details the data. Section 4 provides the results. Section 5 concludes.

2. Model and Estimation

2.1 Model

We develop a simple game-theoretic model of ATM firm and consumer behavior that we estimate using data on ATM locations. The unit of observation is a county and our model is static. We feel that a static model is appropriate since sunk costs in the ATM industry are low: machines can be resold, and ATMs are often installed within existing retail establishments.

There exists a set of potential ATM locations $j = 1, \ldots, J$, each with an entrepreneur. Each entrepreneur simultaneously decides whether to install an ATM at her location. In Minnesota, each entrepreneur also chooses her price conditional on entry at the same time as the entry decision. Our model of firms abstracts away from all notions of banks and considers a firm to be an entrepreneur. Thus, we do not consider any strategic effect of firms with multiple ATMs. We feel that this is a reasonable approximation because the ATM entry decision is often made by individual retail establishments. Thus, while a bank with multiple ATMs might hesitate to set up

a new ATM because it might steal business from its existing machines, our view is that a merchant, who does not have to worry about business stealing, could set one up at a similar cost.[6]

Consumers, denoted $i = 1, \ldots, I$, observe the set of actual ATMs as well as the posted price for each ATM. In Iowa, these prices are fixed at zero, although the regulated price that the ATM receives from the transaction (which we call the interchange fee) is positive. Consumers then make a decision of which ATM to use, if any.

We do not model the fact that the consumer's bank may charge a fee in addition to the fee charged by the ATM, or otherwise induce consumers to use their ATMs. This is one important limitation of our model of ATMs as entrepreneurs. We now detail the specifics of the consumer and firm problems.

Consumers make a discrete choice from among the ATMs in the county. To capture the fact that with more ATMs, consumers will be more likely to use an ATM, we specify an outside alternative whose utility we normalize, $u_{i0} = 0$. The outside option corresponds to using a bank teller instead of an ATM, or of not obtaining cash.

The utility from using an ATM depends on the distance between the consumer and the ATM as well as on price. Specifically, we let this utility be:

(1) $u_{ij} = \delta + \alpha d_{ij} + \beta p_j + \sigma_c \varepsilon_{ij}$,

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[6] Note that this is approach is different from Seim (2002)'s approach. She assumes that each video store entrepreneur chooses one census tract from the set of tracts in the county. The difference in approaches stems from the fact that we feel that existing retail establishments are a reasonable universe for the set of potential ATM locations, while the set of potential video store locations is more open.

where d_{ij} is the distance from consumer i's location to ATM j's location, p_j is the price charged by ATM j, δ is the gross mean benefit from using the ATM, ε_{ij} is an idiosyncratic unobservable, and α and β are parameters that indicate the impacts of price and distance on utility, respectively. As is generally true in discrete choice models, we cannot separately identify σ_c. Hence, we exclude σ_c when estimating (1). The other parameters (δ, α and β) should be interpreted as their true values divided by σ_c.

We assume that ε_{ij} is distributed Type I extreme value, which gives rise to the standard multinomial logit expected quantity formula for consumer i at firm j conditional on entry by firm j:

$$(2) \qquad s_{ij}\left(\alpha, \beta, \delta, n, p\right) = \frac{\exp\left(\delta + \alpha d_{ij} + \beta p_j\right)}{1 + \sum_{k \neq j} n_k \exp\left(\delta + \alpha d_{ik} + \beta p_k\right) + \exp\left(\delta + \alpha d_{ij} + \beta p_j\right)},$$

where n_k is a 0-1 indicator for whether potential entrant k has entered.

We now turn to the model of potential entrants. Each potential entrant must decide whether to enter at her location, and will enter if her expected profits from entry are positive. We assume that the marginal cost of an ATM transaction is zero. We make this assumption because, except in very crowded locations where there is queuing and hence a shadow cost of usage of an ATM, the marginal cost of using an ATM is trivial, consisting roughly of the small amount of ink and paper used to print a receipt. Hence, the expected profits are given by the expected number of transactions times price minus the fixed cost of entry:

(3) $$E\left[\pi_j\right] = \sum_{i=1}^{I} E\left[s_{ij}\left(\alpha,\beta,\delta,n,p\right)\right] \times \left(p_j + p^{interchange}\right) - F_j .$$

The expected number of ATM transactions conditional on entry can be derived by summing (2) over the set of consumers $i = 1,\ldots,I$. In contrast to marginal costs, the fixed costs of ATMs are likely large, consisting mostly of cash deliveries by armored truck. Moreover, the fixed costs of ATMs are likely to differ by location, since the costs of sending armored trucks will vary by location. We model mean fixed costs via local fixed effects. Our specification is:

(4) $$F_j = c + c_b atbank_j + \sigma_e e_j$$

where c is a fixed effect common to all banks in the county, $atbank_j$ is a dummy variable indicating whether the location of potential entrant j is a bank, c_b is a cost shifter for being at a bank, e_j is an idiosyncratic component of fixed cost, that we assume to be distributed logit (i.e. as the difference of two i.i.d. Type 1 extreme value random variables), and σ_e is the standard deviation shifter for this idiosyncratic component. To capture the local variation in costs, we allow c to take on different values for different counties in some specifications.

We assume that e_j is known to entrepreneur j at the time of her entry decision. However, we assume that firm j does not know the fixed cost shocks for the other potential entrants. The use of unobservable cost shocks of this type is common in the entry literature,[7] as it helps reduce the number of equilibria for entry models.

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[7] See, for instance, Seim (2002) and Augereau, Greenstein and Rysman (2002).

The incomplete information about the cost shocks implies that it is meaningful to consider a Bayesian-Nash equilibrium (BNE). In Iowa, a BNE specifies the entry decision for each type e_j for each firm, $j = 1, \ldots, J$. It is easy to show that any BNE is characterized by a vector of cutoffs $\bar{e}_1, \ldots, \bar{e}_J$, whereby firm j will enter if and only if $e_j \le \bar{e}_j$. Let $\Pr(in_j | \bar{e}_j)$ denote the ex-ante probability of a firm's action given the cutoff, before the actual u draws are realized. The logit assumption implies that the density of in_j can easily be expressed in terms of $\bar{e}_j$. For instance, $\Pr(in_j = 1 | \bar{e}_j) = \frac{\exp(\bar{e}_j)}{1 + \exp(\bar{e}_j)}$. Using these cutoffs, the vector of BNE cutoffs must satisfy:

(5)
$$
\begin{aligned}
0 = E[\pi_j] = \sum_{n_1=0,1} \cdots \sum_{n_{j-1}=0,1} \sum_{n_j=1} \sum_{n_{j+1}=0,1} \cdots \sum_{n_J=0,1} \Pr(in_1 = n_1 | \bar{e}_1) \\
\times \ldots \times \Pr(in_{j-1} = n_{j-1} | \bar{e}_{j-1}) \times \Pr(in_{j+1} = n_{j+1} | \bar{e}_{j+1}) \times \ldots \times \Pr(in_J = n_J | \bar{e}_J) \\
\times \sum_{i=1}^{I} s_{ij}(\alpha, \beta, \delta, n, p^{Iowa}) \times p^{interchange} - (c_j + \sigma_e \bar{e}_j), \quad j = 1, \ldots, J,
\end{aligned}
$$

where $p^{interchange}$ is the regulated interchange fee.

The equilibrium conditions are slightly more complicated for Minnesota. For Minnesota, each firm must choose a price together with an entry strategy. As a Bertrand competitor, firm j must choose its price to satisfy the FOC of its profits with respect to its price, conditional on entry and the decisions of other firms. This FOC can be written:

(6)
$$
\begin{aligned}
0 = \frac{\partial E[\pi_j]}{\partial p_j} = \frac{\partial}{\partial p_j} \Bigg[\sum_{n_1=0,1} \cdots \sum_{n_{j-1}=0,1} \sum_{n_j=1} \sum_{n_{j+1}=0,1} \cdots \sum_{n_J=0,1} \Pr(in_1 = n_1 | \bar{e}_1) \times \ldots \times \Pr(in_{j-1} = n_{j-1} | \bar{e}_{j-1}) \\
\times \Pr(in_{j+1} = n_{j+1} | \bar{e}_{j+1}) \times \ldots \times \Pr(in_J = n_J | \bar{e}_J) \times \sum_{i=1}^{I} s_{ij}(\alpha, \beta, \delta, n, p) \times (p^{interchange} + p_j) \Bigg].
\end{aligned}
$$

The BNE for Minnesota must satisfy two sets of conditions. First, it must satisfy conditions that are analogous to (5), except with the equilibrium price vector instead of p^{Iowa}. Second, it must satisfy the FOCs in (6). Although firms are free to choose a different price for each realization of e_j, e_j only affects the fixed costs and hence does not enter into the FOC (6). Thus, in general, the BNE price will not depend on e_j.

2.2. Estimation and identification

In order to evaluate the impact of ATM surcharges on consumer welfare and ATM entry, we develop a method to obtain estimates of the parameters, which we group together as $\theta = (\alpha, \beta, \delta, c, \sigma_e)$. Recall that c is a vector in some specifications, as the mean fixed costs vary across counties, in (4).

Our basic estimation strategy is to estimate the Iowa model first, as this estimation procedure is conceptually and computationally simpler. We then make the identifying assumptions that fixed costs for border counties in Minnesota are similar to costs for the corresponding Iowa border counties, and that consumers' preferences are similar across the two regions. This implies that, after estimating the Iowa model, the only unknown parameter is the price coefficient α. We then estimate this coefficient using the Minnesota data.

A potential method for estimating the Iowa model would be to use maximum likelihood. Similarly to Seim (2002), we could find the likelihood for a given parameter vector and a given county by solving for the equilibrium entry probabilities, using (5). Let y_j denote a 0-1 indicator

for whether firm j entered. If we assume that there is a unique vector of equilibrium cutoffs for the parameter vector θ, then we can write the likelihood for the county as:

$$(7) \qquad \ln L(y, \theta) = \sum_{j=1}^{J} \ln \left(\Pr \left(in_j = y_j \middle| \bar{e}_j (\theta) \right) \right),$$

where the $\bar{e}$ cutoffs are recomputed to satisfy (5) for any θ. Note that the cutoffs, and hence the likelihood, implicitly depend on the exogenous data in the county, which are the locations of the entrepreneurs and consumers.

Although this method can potentially estimate the parameters of interest, it is very computationally intensive because it requires the computation of the equilibrium cutoffs for each parameter vector and each county. Moreover, the likelihood is not well defined for cases where there are multiple equilibria.

Thus, instead of directly maximizing the likelihood, we use the method proposed by Aguirregabiria and Mira (2002). The idea of this method is to substitute the probabilities of competitors' actions from the data instead of solving for these probabilities in equilibrium. In our case, (5) shows that firm j's actions depends on competitors' actions only through $\Pr(in_k), k \neq j$. Moreover, by the construction, these probabilities depend only on observable data. As the data is assumed to be generated by the equilibrium of the model at the true parameter values, the entry probabilities in the data conditional on observable characteristics will reflect the equilibrium entry probabilities.

We implement this method by substituting the entry probabilities from the data into (5):

$$(8) \quad \Pr\left(in_j = 1 \big| \theta\right) = \Pr\left(\sum_{n_1=0,1} \cdots \sum_{n_{j-1}=0,1} \sum_{n_j=1} \sum_{n_{j+1}=0,1} \cdots \sum_{n_J=0,1} \widehat{\Pr}\left(in_1 = n_1\right) \times \ldots \times \widehat{\Pr}\left(in_{j-1} = n_{j-1}\right) \times \right.$$

$$\left. \widehat{\Pr}\left(in_{j+1} = n_{j+1}\right) \times \ldots \times \widehat{\Pr}\left(in_J = n_J\right) \times \sum_{i=1}^{I} s_{ij}\left(\alpha, \beta, \delta, n, p^{\text{Iowa}}\right) \times p^{\text{interchange}} - \left(c_j + \sigma_e e_j\right) > 0 \right),$$

where $\widehat{\Pr}\left(in_k = n_k\right), k \neq j$ are the entry probabilities in the data. We obtain $\widehat{\Pr}\left(in_k\right)$ via an initial

reduced-form estimation, and then evaluate the likelihood for θ by substituting (8) into (7). Note

that the only random variable in (8) is e_j, which is distributed as a logit. Thus, conditional on

obtaining the non-random part of (8) (which depends on the complicated sum of competitors'

actions) it is straightforward to evaluate the probability of entry in (8).

It is computationally difficult to solve for the non-random part of (8), because it involves

a sum over 2^{J-1} terms, and J, the number of potential ATM locations, is often of size 10 or 20,

even for rural counties in Iowa. Thus, we evaluate this sum using simulation. Specifically, we

take uniform draws and convert them to a 0-1 realization of entry based on $\widehat{\Pr}\left(in_k\right)$. We estimate

our model with 10 simulation draws. We experimented with using more simulation draws, but

found little change in the likelihood, which is probably because of the simple, discrete nature of

the integral. As is standard in the literature, we use the same draws across different parameter

values.

We maximize the likelihood function using the derivative-based Newton method. We did

not experience any convergence problems, probably because the actual likelihood function is

similar to a logit. We compute standard errors for the parameter estimates using the standard

approximation based on the sum of the outer-product of the derivatives of the individual

contributions to the log likelihood.

One important detail is how to compute the reduced-form probabilities of entry, $\widehat{\Pr}(\text{in}_k)$.

We estimate these probabilities by performing a reduced-form logit estimation of entry on exogenous data, and then taking the fitted values as $\widehat{\Pr}(\text{in}_k)$. Ideally, we would like to include a non-parametric expansion of the exogenous data, but the dimensionality of the characteristics space is too large. We include in this reduced-form logit estimation the number of consumers within each of 5 distance bands (.1, .5, 1, 2, and 5 kilometers), the number of other potential entrants within these same distance bands and interactions of these two variables. We examine the reasonableness of our reduced-form model by simulating equilibrium data, performing this reduced-form estimation on the simulated data, and comparing $\widehat{\Pr}(\text{in}_k)$ to $\Pr(\text{in}_k)$ for these data.

We now turn to the estimation of the Minnesota data. As noted above, the only parameter to estimate is α. Just as we could have estimated the Iowa model with maximum likelihood by solving for the BNE conditional on parameters, we can estimate the Minnesota model with maximum likelihood by solving for the BNE using (6) and the analog of (5). However, we cannot directly apply the same Aguirregabiria and Mira (2002) method to solve for the Minnesota data. The reason is that, unlike entry decisions, we do not observe price. Hence, we cannot substitute competitors' prices in the same way that we substitute competitors' entry decisions in Iowa.

However, even for Minnesota, we can directly substitute the entry probabilities from the data for the equilibrium entry probabilities, as we do for Iowa. After doing this, (6) becomes

$$
(9) \quad 0 = \frac{\partial}{\partial p_j} \left[\sum_{n_1=0,1} \cdots \sum_{n_{j-1}=0,1} \sum_{n_j=1} \sum_{n_{j+1}=0,1} \cdots \sum_{n_J=0,1} \widehat{Pr}\left(in_1 = n_1\right) \times \ldots \times \widehat{Pr}\left(in_{j-1} = n_{j-1}\right) \times \right.
$$

$$
\left. \widehat{Pr}\left(in_{j+1} = n_{j+1}\right) \times \ldots \times \widehat{Pr}\left(in_J = n_J\right) \times \sum_{i=1}^{I} s_{ij}\left(\hat{\alpha}, \hat{\beta}, \hat{\delta}, n, p\right) \times \left(p^{interchange} + p_j\right) \right], \, j = 1, \ldots, J,
$$

where the parameters with a hat represent the estimated values of the parameters from the Iowa data. We solve for the equilibrium vector of prices p^{eqm} by finding the vector of prices that simultaneously solve the FOCs in (9). We then define the probability of entry analogously to (8) as:

$$
Pr\left(in_j = 1 \middle| \alpha\right) =
$$

$$
(10) \quad Pr\left(\sum_{n_1=0,1} \cdots \sum_{n_{j-1}=0,1} \sum_{n_j=1} \sum_{n_{j+1}=0,1} \cdots \sum_{n_J=0,1} \widehat{Pr}\left(in_1 = n_1\right) \times \ldots \times \widehat{Pr}\left(in_{j-1} = n_{j-1}\right) \times \widehat{Pr}\left(in_{j+1} = n_{j+1}\right) \right.
$$

$$
\left. \times \ldots \times \widehat{Pr}\left(in_J = n_J\right) \times \sum_{i=1}^{I} s_{ij}\left(\hat{\alpha}, \hat{\beta}, \hat{\delta}, n, p^{eqm}\right) \times \left(p^{eqm} + p^{interchange}\right) - \left(\hat{c}_j + \hat{\sigma}_e e_j\right) > 0 \right).
$$

We then evaluate the likelihood by substituting from (10) into the analogous expression to (7). We maximum the likelihood for this parameter using a non-derivative based simplex method.

Even though we need to solve for p^{eqm} to evaluate (10), our substitution of the entry probabilities from the data simplifies the equilibrium computation, since we do not have to solve for the entry probabilities. As with the Iowa data, we evaluate (9) and (10) using simulation. Even with simulation methods and the substitution for the exogenous entry probabilities, evaluating the likelihood for Minnesota is very computationally intensive. However, our overall computation time is lessened by the fact that we only have to estimate one parameter with this method.

Importantly, the reduced-form relationship between the entry probability and exogenous variables will be different in Minnesota from in Iowa, because of the difference in the nature of competition. However, the exogenous observable data remain the same. Hence, we estimate different reduced-form coefficients for Minnesota, but using the same reduced-form model as for Iowa.

One potential issue is the possibility of multiple equilibria. Multiple equilibria are particularly likely when the standard deviation of the idiosyncratic components of profits, σ_e, is small. For instance, with small σ_e, if there are two entrants at a given location, then it may be profitable for exactly one entrant to enter, but not for both. Multiple equilibria are often a problem in entry models, for this reason.[8] Multiple equilibria are less likely in our model when there are sizable unobservable idiosyncratic components of profits. Moreover, one additional advantage of our estimation strategy is that it is robust to certain types of multiple equilibria. To see this, note that if the reduced-form logit estimation provides the same predictors of entry probabilities as firms in the industry perceive, then it will be consistent with the equilibrium that generated those entry probabilities, and hence an estimation based on these probabilities will yield consistent estimates. As an example, if it is always the case that the equilibrium entry selection specifies that firms enter in order of most to least profitable based on observable variables, then a sufficiently rich reduced-form model will capture this equilibrium behavior.

We briefly discuss the identification of the parameters. Our Iowa estimation will identify the consumer parameters (on disutility of distance and mean utility) based on the relationship between the variation in the entry probability for potential entrants and the density of nearby population. The parameters on the mean and standard deviation of the fixed costs of entry will be

identified based on how likely firms are to enter and on the amount of idiosyncratic variance in their entry decisions. The parameter on the bank shifter to the fixed costs of entry will be identified based on the relative probabilities of entry for ATMs at banks to grocery stores.

In general, the scale in a discrete-choice model is not well-defined. However, in our case, the scale of the profit function can be identified. The reason for this is that the scale is tied down by $p^{interchange}$, which we take from the data and express in dollar units. This normalization is what allows to estimate σ_e.

Last, the consumer parameter on disutility of price will be identified from the quasi-experimental variation created by the state-level policy differences together with the assumption that the fundamental cost and utility parameters are very similar for the border counties across the state line. For example, if we see relatively much less entry in Minnesota in areas with many potential entrants, this will imply that demand is very elastic, causing the margins from entry to fall with more firms.

3. Data

We use three principal sources of data: data on ATM locations, data on potential ATM locations, and data on consumer locations. Our data come from the year 2002. We discuss each of these data sources in turn.

Our first data set provides the set of potential ATM locations. ATMs are almost certain to be inside other retail establishments, particularly in the rural counties from our sample. We obtained phone numbers of all the retail establishments for one county in Iowa, using the web

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[8] See, for instance, Berry (1992) and Andrews and Berry (2002).

site switchboard.com. By calling every retail establishment in that county, we found that the ATMs were all located in grocery stores (including convenience stores) or banks. Based on this initial exercise, we chose grocery stores and banks as the set of potential ATMs. We obtained the addresses and phone numbers of grocery stores and banks for our counties from a private company called InfoUSA, which markets this information for commercial use. We then geocode these addresses to obtain detailed latitude and longitude information.

Our second data are information on the locations of ATMs. We obtained location data from several large ATM networks with substantial operations in Minnesota and Iowa. The networks in our data set include Visa Plus, a network that is national in scope, and SHAZAM, which is based in Iowa and has ATMs throughout the Central States.[9] The data provide the address of ATMs for all machines in the databases of the networks. However, we found that these data were incomplete, primarily in Minnesota. Thus, we are in the middle of calling each of the grocery stores and banks from the InfoUSA database to determine if they had an ATM in 2002.

Our third data set provides the locations for consumers. These data are from the 1990 Census, and provide the location of consumer residences at the census block level. This level is not quite as fine as the address level, but still very small.

As our model is identified by the difference in the pattern of ATM diffusion for Minnesota and Iowa, we want to ensure that the counties on either side of the border are similar, in terms of consumer preferences and firm costs. In order to ensure that we have similar counties, we keep the border counties from each state as well as counties that are within one county of the border. Figure 1 provides this set of counties as well as indicating the population density for each

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[9] We thank these networks for providing us with data.

county; a darker shade represents a denser population. Several of the counties in the eastern part of Minnesota are much denser than the corresponding Iowa counties. These are counties that border on medium-sized cities, such as Rochester. We feel that the dense counties are sufficiently different from the corresponding Iowa counties, and so we exclude the eight densest Minnesota counties from our sample.

Figure 1 also indicates the locations of actual ATMs in our sample. As we would expect, more densely populated counties also tend to have a greater density of ATMs.

For some of our estimates, we allow the entire border region to have the same mean fixed costs for ATMs. For other estimates, we allow the mean fixed costs to vary across counties. For these estimates, we group the mean fixed costs so that the Iowa border county and its Southern neighbor (e.g. Lyon and Sioux, respectively) share the same fixed costs. For all of our estimates, the unit of observation remains the county. Thus, firms compete exclusively with other firms in the county and exclusively for customers that live in the county.

In the estimation we assume that the interchange fee, $p^{interchange}$, is \$.35. In reality, the interchange fees vary slightly across networks, but are in the \$.30-\$.40 range. In the case where an ATM and a customer's bank both use multiple networks, the actual interchange fee will vary based upon the agreements between the ATM and the different networks. The value of $p^{interchange}$ will not affect the coefficient estimates in the Iowa analysis, as expected profits in (5) are proportional to $p^{interchange}$. However, the chosen value will affect coefficient estimates in Minnesota because, with surcharging, expected profits are now proportional to the sum of the interchange fee and the entering firm's price.

Table 1 provides some summary statistics of the data. We have 27 counties in our data, of which 21 are in Iowa. Our counties are not very populated, with an average of about 16,000

people in Iowa, and somewhat less in Minnesota. In spite of their small population, each county contains about 1,000 census blocks, suggesting that the unit of geographic measurement for people is small. In Iowa, there are an average of 14.53 ATMs per county. The corresponding figure for Minnesota is 14.8, suggesting that the unregulated price may result in more entry. There are, on average, about 30 percent less potential ATM locations in Minnesota than in Iowa. The number of actual and potential ATMs varies a lot across counties. For instance, one Iowa county has 48 ATMs and 88 potential ATM locations, while another county has only 15 potential ATM location and 4 ATMs.

4. Results

In order to examine the reasonableness of our method of inference, we first examine the performance of our model on simulated data for 500 simulated counties. Within each county, we simulate data by randomly assigning potential entrant and consumer locations. We then compute the equilibrium entry probability of the model conditional on the exogenous variables and some chosen "true" parameter vector, and simulate the entry decisions from the equilibrium entry probability. Using the simulated data, we then estimate the parameters of the model. The results from the simulated data are presented in Table 2.

The simulated data generates an estimated parameter on distance that matches the true parameter value very closely (-.251 vs. -.228) and has a very small standard error. The other parameters are also precisely estimated and close to their true values.

Also of interest is the performance of our reduced-form predictor of the entry probability. Since we know the true probability of entry for the simulated data from the equilibrium

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computation, we can compare the true probability to the predicted probability. We find a fairly close match between the two, with a root mean squared difference in the probabilities of .121. This, and the closeness of the parameter estimates, suggests that our reduced-form approximation of the true entry probability is reasonable.

We turn now to our base parameter estimates for the real data, which are given in Table 3. The estimates for this table assume that the mean fixed costs are the same across the Minnesota - Iowa border region in our sample. The first set of number provides the parameters that are estimated from Iowa data, while the price coefficient at the bottom is estimated from the Minnesota data. The estimates in this table are generally precisely estimated and appear to be reasonable.

The coefficient of distance on utility is -.213. The magnitude of this coefficient implies that a person who had a 50% chance of using a particular ATM would use it with roughly 45% probability if the ATM were to move 1 kilometer further away. This coefficient is likely reasonable, for a sample that consists of rural Iowa and Minnesota. The coefficient on price is estimated to be -.958. This implies that the consumer values one extra kilometer of distance as equivalent to $.16, a figure that also appears to be reasonable. The mean fixed costs of operating an ATM not at a bank is estimated at $194 with a standard deviation term of $136. The mean fixed costs of operating an ATM at a bank is estimated to be trivially higher.

Table 4 provides the alternate specification, where we allow the mean fixed costs to vary across the Iowa counties in the sample. The parameter estimates for this specification are very similar to those from Table 3. Moreover, the coefficients for this specification are also precisely estimated.

Using the parameter estimates, we can evaluate the impact of counterfactual surcharge policies on consumer and firm welfare and the prevalence of ATMs. We do this by postulating counterfactual policy regimes, and simulating the equilibrium entry decisions given these policy regimes. For any vector of firm entry decisions, we can evaluate the expected consumer welfare and firm profits using the standard multinomial logit formulas. The consumer welfare measures are in utils. However, we can convert them to dollars by dividing them by the estimated marginal utility of money, which is $-\beta$. This then allows us to add consumer and producer surplus.

Table 5 provides the results of these counterfactual experiments, evaluated using the parameters of Table 3. We find that a surcharge ban would increase the average number of entrants from 6.40 to 9.20, a ratio that is roughly consistent with the relative population-weighted prevalence of ATMs in the Iowa and Minnesota counties that we study. The surcharge ban reduces total consumer surplus by about $1,100, and increases producer surplus by about $150. Thus, the mean effect is to lower total surplus about $950 or roughly 20 percent. The implication is that, on average, consumers value the convenient of additional ATMs more than the convenience due to lower prices that occurs in equilibrium when surcharges are banned. Producers earn slightly more profits without surcharges, but the difference in producer surplus is much smaller.

5. Conclusion

We have developed a structural model of ATM utility, costs and entry. Our model is static and assumes single-product firms. Our specification of utility includes travel distance and price. We assume that potential entrant firms enter based on the total revenues from entering

minus the fixed costs; we assume that marginal costs are zero. We also assume that a firm's fixed cost is private information that is not revealed to other firms in the industry. Firms entry decisions are based on the Bayesian-Nash equilibrium of their entry game.

We develop a method to estimate the parameters of this model using data on the locations of consumers, potential ATM locations and actual ATMs. Our method of inference obtains estimates of our game-theoretic model of entry without solving for the equilibrium of the game, and hence is computationally very efficient. Our estimation procedure is identified by the fact that the State of Iowa fixed the surcharge price of ATMs at zero during our sample period. This allows us to estimate most of the parameters from Iowa data, without worrying about the price elasticity. We then make the assumption that consumer preferences and costs for counties in Minnesota and Iowa near their border are similar. By substituting the parameters estimated using Iowa data, we then recover the price elasticity using the Minnesota data.

We first analyze the performance of our estimation procedure by examining simulated data. The procedure appears to be reasonable. With simulated data, our reduced-form model of entry captures the true entry probability reasonably closely, and hence the maximum likelihood estimates are able to recover the true parameters reasonably well. Turning to the real data, we find a coefficient on distance that is significantly negative, and moderate in size. The consumer tradeoff between price and distance also fits our expectations. We use these estimates to find the welfare and entry consequences of an ATM surcharge ban. We find that a surcharge ban would moderately increase the number of ATMs, decrease consumer surplus, increase firm surplus and decrease total surplus.

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Table 1:
Summary statistics of the data by county

Statistic	Mean	Std. Dev.	Min	Max	N
Potential ATM locations, IA	33.7	16.8	15	88	21
Actual ATMs, IA	14.53	10.47	4	48	21
Consumers, IA	16,384	8,720	7,267	46,733	21
Census blocks with people, IA	988.1	315.8	563	1,727	21
Potential ATM locations, MN	21.5	5.89	15	32	6
Actual ATMs, MN	14.8	3.31	10	20	6
Consumers, MN	12,404	3,943	9,660	20,098	6
Census blocks with people, MN	831.2	187.6	582	1,124	6

Table 2:
Results from simulated equilibrium data

Parameter	Estimate	Standard Error	True Value
Std. dev. of unobserved profits (σ_e) (Units: $100)	.836***	.089	.839
Utility from distance (α) (Units: kilometers)	-.251***	0.026	-.228
Consumer benefit (δ)	-.853***	.224	-1.03
Extra fixed cost if ATM is at a bank (c_b)	-.919***	.119	-.919
Mean fixed cost (c) (Units: $100)	2.04***	.229	1.88
Number of counties		500	
Mean number of potential entrants (std. dev.)		5.53 (2.85)	
Mean number of actual entrants (std. dev.)		3.43 (2.21)	
Mean number of consumers (std. dev.)		6,354 (3,659)	
Root mean squared difference, true and predicted entry probs.		.121	
Log likelihood		-1375.26	

*** Significant at 1% level

Table 3:
Results for model with same mean fixed costs across counties

Parameter	Estimate	Standard Error
From Iowa data		
Std. dev. of unobserved profits (σ_e) (Units: \$100)	1.36***	.216
Utility from distance (α) (Units: kilometers)	-.213**	.097
Consumer benefit (δ)	-1.07**	.522
Extra fixed cost if ATM is at a bank (c_b)	.069	.226
Mean fixed cost (c) (Units: \$100)	1.94***	.390
Log likelihood	-457.4	
From Minnesota data		
Utility from price (β)	-.958***	.102
Log likelihood	-85.7	

*** Significant at 1% level
** Significant at 5% level

Table 4:
Results for model with different mean fixed costs across counties

Parameter	Estimate	Standard Error
From Iowa data		
Std. dev. of unobserved profits (σ_e) (Units: $100)	1.27***	.202
Utility from dist. (in KM) (α)	-.199***	.078
Consumer benefit (δ)	-.528	.576
Extra fixed cost if ATM is at a bank (c_b)	.095	.215
Mean fixed cost FIPS 19005	2.18***	.687
Mean fixed cost FIPS 19033	2.47***	.377
Mean fixed cost FIPS 19037	2.49***	.689
Mean fixed cost FIPS 19041	2.09***	.506
Mean fixed cost FIPS 19063	2.53***	.550
Mean fixed cost FIPS 19065	2.15***	.702
Mean fixed cost FIPS 19067	3.61***	.793
Mean fixed cost FIPS 19081	3.21***	3.45
Mean fixed cost FIPS 19109	2.82***	3.81
Mean fixed cost FIPS 19119	2.30***	3.89
Mean fixed cost FIPS 19141	2.20***	3.65
Log likelihood	-444.4	
From Minnesota data		
Utility from price (β)	-1.48***	.161
Log likelihood	-86.6	

* Significant at 10% level

Table 5:
Results of counterfactual policy experiments

Statistic	Policy: Ban on ATM Surcharges	Policy: ATM Surcharges Allowed
Producer surplus	$1148 ($257)	$1,006 ($187)
Consumer surplus	$2,883 ($1,205)	$3,955 ($1,574)
Total surplus	$4,030 ($1,458)	$4,962 ($1,755)
Number of actual entrants	6.40 (1.23)	9.20 (1.87)
Number of potential entrants	16.6 (1.72)	
Population	9,422 (1,320)	
N	7	

Note: We include Minnesota and Iowa counties with 10 or less potential entrants in this sample. We compute equilibria using the parameters from Table 3. Standard deviations are reported in parentheses.

Figure 1: Minnesota and Iowa Border Counties, ATMs and Population Density