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

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Problem that we address:

- We seek to understand the impact of automatic teller machine (ATM) surcharges on welfare and entry of ATMs
- We develop a structural model of consumer utility and choice, and ATM costs and entry, and use the model to evaluate the impact of surcharges

Why should we care about ATM surcharges and entry?

- Over the past 20 years, ATMs have become a ubiquitous part of consumer banking
- In spite of their presence, the market for ATMs may not reflect optimal outcomes
- Up to 1996, major networks banned ATM surcharges
- Following the breakdown, large entry of new ATMs, large increase in prices, and lower volume per machine
- Technology of ATMs is high fixed costs and low marginal costs
- Lower volume per machine implies higher average costs

- The rise in prices suggests the possibility of "excess" entry
- Welfare might have been higher with fewer ATMs and lower prices
- But, consumers now have to travel less distance to get to an ATM, which can make them better off
- Theoretically ambiguous whether unregulated market will result in excess entry
- Answer depends on consumer tradeoff between price and distance, firm cost structure and equilibrium interaction
- Structural model can shed light on these questions

The "big picture" of this analysis

- Study can inform us about presence of excess entry in differentiated products markets
- Study builds on literatures on entry models and on excess entry in differentiated products
- We demonstrate how to use sources of quasi-experimental variation to identify structural parameters and get more reasonable answers to these questions
- Methodological part: study develops computationally feasible methods for estimating game theoretic models

Our estimation strategy

- In general, might be difficult to separately identify effect of price and distance using entry data

- We identify these parameters using a source of quasi-experimental variation: The State of Iowa banned ATM surcharges during our sample period

- Neighboring states, such as Minnesota, did not

- Difference in adoption between Iowa and Minnesota creates a source of quasi-experimental variation for border counties

- Other studies have used borders to identify economic parameters (e.g. Holmes (1998), Chay and Greenstone (2003))

Relation to literature

- Study builds on entry literature started by Bresnahan and Reiss (1991) and Berry (1992)

- Like recent papers (Chernew, Gowrisankaran and Fendrick (2001), Mazzeo (2002), Seim (2002)) we include detailed geographic and product-level data

- Some recent work on ATM surcharges: (Hannan, Kiser, McAndrews and Prager (2002), Knittel and Stango (2005), Ishii (2005), and others)

- Recent papers (Davis (2002), Berry and Waldfogel (1999)) empirically analyze whether differentiated products markets have "excess" entry

- Methodology most similar to Seim's work on video-store entry
- However, we model entry as an explicit function of fundamental utility and cost parameters
- Questions that we can answer are very different
- Develop new econometric techniques that vastly reduce computational burden of estimating model

Model:

- Unit of observation is county or border region
- Static model of ATM entry and usage
- Potential ATM locations $j = 1, \ldots, J$
- Consumer locations $i = 1, \ldots, I$
- Each location is controlled by an individual entrepreneur
- Entrepreneur decides whether or not to open an ATM
- We don't consider strategic effect of firms with multiple ATMs

Consumer model:

- Consumers observe set of actual ATMs and posted price for each ATM
- They make a discrete choice of which ATM to use, if any
- There is an outside option, where they use no ATM
- In Iowa, price is fixed at zero
- However, the ATM receives a fixed positive fee from the transaction, called the interchange fee

Consumer utility function:

$$u_{ij} = \delta + \alpha d_{ij} + \beta p_j + \sigma_c \varepsilon_{ij}$$
$$u_{i0} = 0$$

where:

– d_{ij} is distance
– p_j is price
– δ is the gross mean utility from an ATM
– ε_{ij} is a Type I extreme value idiosyncratic shock
– σ_c, the standard deviation of the shock, is normalized to 1

- We estimate δ, α, and β
- Big limitation: we don't model price charged by customer's bank

- This gives rise to the standard multinomial expected quantity formula for firm j conditional on entry by firm j:

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

where n_k is an indicator for whether firm k has entered

Potential entrant profit function:

- We assume that marginal costs per ATM transaction are zero
- This results in expected profits conditional on entry of:

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

where F_j are fixed costs,

$$F_j = c_j + \sigma_e e_j, \;\text{ and }\; c_j = \gamma_{\text{county } j} + \gamma'_{\text{atbank } j}$$

- Mean fixed costs c_j vary across county and bank vs. non–bank potential ATM location

- We assume that e_j is distributed as a logit and known to entrepreneur j at the time of her entry, but not known to her competitors

- The use of unobservable cost shocks of this type is common in the entry literature; it helps reduce the number of equilibria

- In Iowa, potential entrants simultaneously choose entry

- In Minnesota, they simultaneously choose entry and price

- Incomplete information about costs gives rise to a Bayesian-Nash equilibrium (BNE)

Characteristics of BNE for our model in Iowa

- For each firm j, there exists cutoff $\bar{e}_j$ such that firm j enters if and only if $e_j \le \bar{e}_j$
- Define probability of entry as $\Pr\left(in_j \middle| \bar{e}_j\right)$
- By logit assumption, probability of entry satisfies

$$\Pr\left(in_j = 1 \middle| \bar{e}_j\right) = \frac{\exp\left(\bar{e}_j\right)}{1+\exp\left(\bar{e}_j\right)}$$

- Expressed in terms of $\bar{u}_j$, the Iowa BNE conditions are:

$$0 = E\left[\pi_j\right] = \sum_{n_1=0,1} \cdots \sum_{n_{j-1}=0,1} \sum_{n_j=1} \sum_{n_{j+1}=0,1} \cdots \sum_{n_J=0,1} \Pr\left(in_1 = n_1 \middle| \bar{e}_1\right)$$

$$\times \ldots \times \Pr\left(in_{j-1} = n_{j-1} \middle| \bar{e}_{j-1}\right) \times \Pr\left(in_{j+1} = n_{j+1} \middle| \bar{e}_{j+1}\right) \times \ldots \times \Pr\left(in_J = n_J \middle| \bar{e}_J\right)$$

$$\times \sum_{i=1}^{I} s_{ij}\left(\alpha, \beta, \delta, n, p^{\text{Iowa}}\right) \times p^{\text{interchange}} - \left(c_j + \sigma_e \bar{e}_j\right),\ j = 1, \ldots, J,$$

Characteristics of BNE for our model in Minnesota

- There is an analogous FOC with respect to entry as for Iowa
- There is also a FOC with respect to price:

$$0 = \frac{\partial E\left[\pi_j\right]}{\partial p_j} = \frac{\partial}{\partial p_j}\left[\sum_{n_1=0,1}\cdots\sum_{n_{j-1}=0,1}\sum_{n_j=1}\sum_{n_{j+1}=0,1}\cdots\sum_{n_J=0,1}\Pr\left(in_1 = n_1 \middle| \bar{e}_1\right)\right.$$

$$\times\ldots\times\Pr\left(in_{j-1} = n_{j-1} \middle| \bar{e}_{j-1}\right)\times\Pr\left(in_{j+1} = n_{j+1} \middle| \bar{e}_{j+1}\right)\times\ldots\times$$

$$\left.\Pr\left(in_J = n_J \middle| \bar{e}_J\right)\times\sum_{i=1}^{I} s_{ij}\left(\alpha,\beta,\delta,n,p\right)\times\left(p^{\text{interchange}} + p_j\right)\right].$$

- Note that price does not change as the type e_j changes

Estimation problem

- Parameters of the model:

  $$\theta = \left(\alpha, \beta, \delta, \gamma, \sigma_e\right)$$

- Endogenous variable:

  Entry decision y_j

- Exogenous variables:

  Locations of potential ATM entrants and consumers

Potential estimation strategy: maximum likelihood

- As in Seim (2002), could find likelihood for a given parameter vector and given county by solving for the equilibrium entry probability

- Then, the likelihood can be expressed:

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

- Method very computationally intensive, as it requires solving for equilibrium for each parameter vector and each county

Idea of our method:

- We adapt techniques developed in other contexts by Hotz and Miller (1993), Aguirregabiria and Mira (2002), Berry and Pakes (2003) and Guerre, Perrigne and Vuong (2000)
- Instead of finding probabilities of competitors' actions in equilibrium, we substitute the probabilities of these actions that are in the data
- Method is appropriate here because, by construction, probabilities depend only on observable data, and data is assumed to be generated from model at true parameters

Implementation of estimation method for Iowa:

- Estimate non-parametric reduced-form entry probabilities

- Substitute these entry probabilities into Iowa BNE conditions:

$$\Pr\left(in_j = 1 \middle| \theta\right) = \Pr\left(\sum_{n_1=0,1} \cdots \sum_{n_{j-1}=0,1} \sum_{n_j=1} \sum_{n_{j+1}=0,1} \cdots \sum_{n_J=0,1} \widehat{\Pr}\left(in_1 = n_1\right) \right.$$
$$\times \ldots \times \widehat{\Pr}\left(in_{j-1} = n_{j-1}\right) \times \widehat{\Pr}\left(in_{j+1} = n_{j+1}\right) \times \ldots \times \widehat{\Pr}\left(in_J = n_J\right) \times$$
$$\left. \sum_{i=1}^{I} s_{ij}\left(\alpha, \beta, \delta, n, p^{Iowa}\right) \times p^{interchange} - \left(c_j + \sigma_e e_j\right) > 0 \right)$$

- Plug these entry conditions into likelihood expression

Important details:

- We estimate the reduced-form competitor entry probabilities $\widehat{\Pr}\left(in_k = n_k\right), k \neq j$ using fitted values from an initial reduced-form logit estimation

- Reduced-form includes number of potential entrants, consumers, potential at-bank entrants and interactions within .2, 1, 2, 5, 10, and 20 kilometers in this initial estimation

- We use simulation to approximate the sum on the previous page

- Some specifications estimate the entire border region at once. This avoids the issue of sites on the border of two counties. For these specifications, we restrict choices to be a function of people and potential ATMs within 50 kilometers.

- We calculate standard errors using standard method; we don't (yet) worry about fact that use of fitted values from initial regression adds noise

Implementation of estimation method for Minnesota:

- Identifying assumption: costs and preferences are similar to region across the border in Iowa
- We use same structural parameters as for Iowa
- Thus, we have only one parameter to estimate: price coefficient
- We don't observe prices, and hence we can't directly substitute in competitors' actions
- However, we still substitute entry probabilities for competitors
- We then compute equilibrium price, find the probability of entry at equilibrium price and maximize the likelihood function

Multiple equilibria:

- Entry models often have multiple equilibria
- Particularly true when σ_e is small
- For instance, with two identical firms, it may be profitable for either to enter, but not both
- Our estimation strategy is robust to multiple equilibria if the equilibrium selection conditions on observables

Identification:

- Using just entry data, variation in entry across number of firms and number of consumers will semi-parametrically identify distribution of fixed costs and δ using Iowa data
- Locations within Iowa will further identify distance elasticity
- In general, scale of discrete-choice model is not identified. We express $p^{\text{interchange}}$ in dollar units, which ties down scale
- Price elasticity of demand identified from quasi-experimental variation in state-level policies and assumption that costs and preferences are similar across state border
- Monte Carlo evidence on identification

Data:

- Three principal sources of data

1) ATM addresses from Visa Plus and SHAZAM and phone calls

2) Addresses of retail establishments from InfoUSA

3) Number of consumers in each census block from U.S. Census

- We keep border counties and counties that are one in from the border

- Figure 1 shows map of counties; Figure 2 has ATMs for two counties

Figure 1: Minnesota and Iowa Border Counties, Population Density

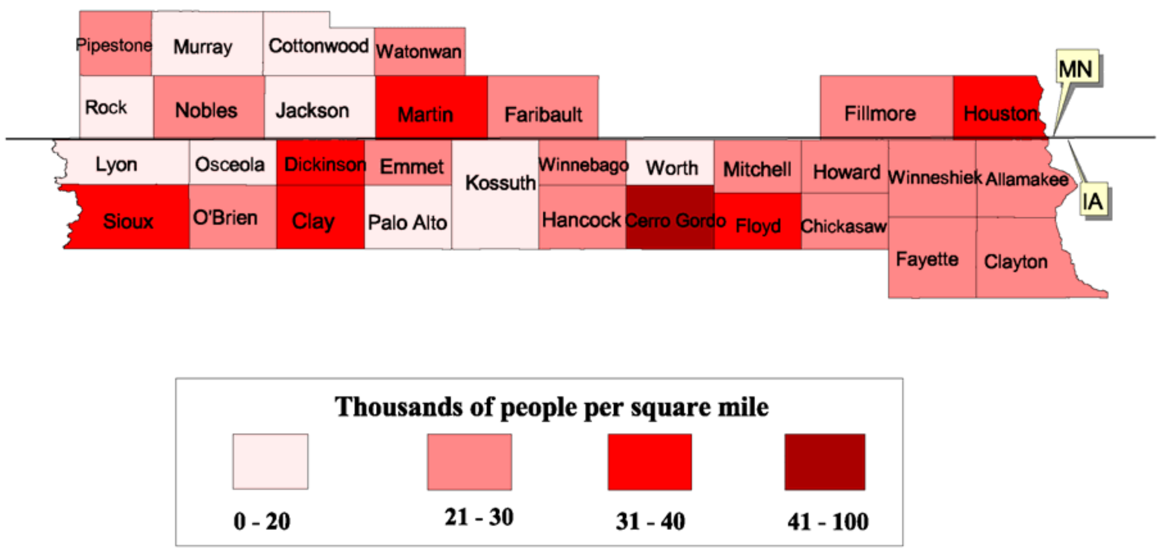
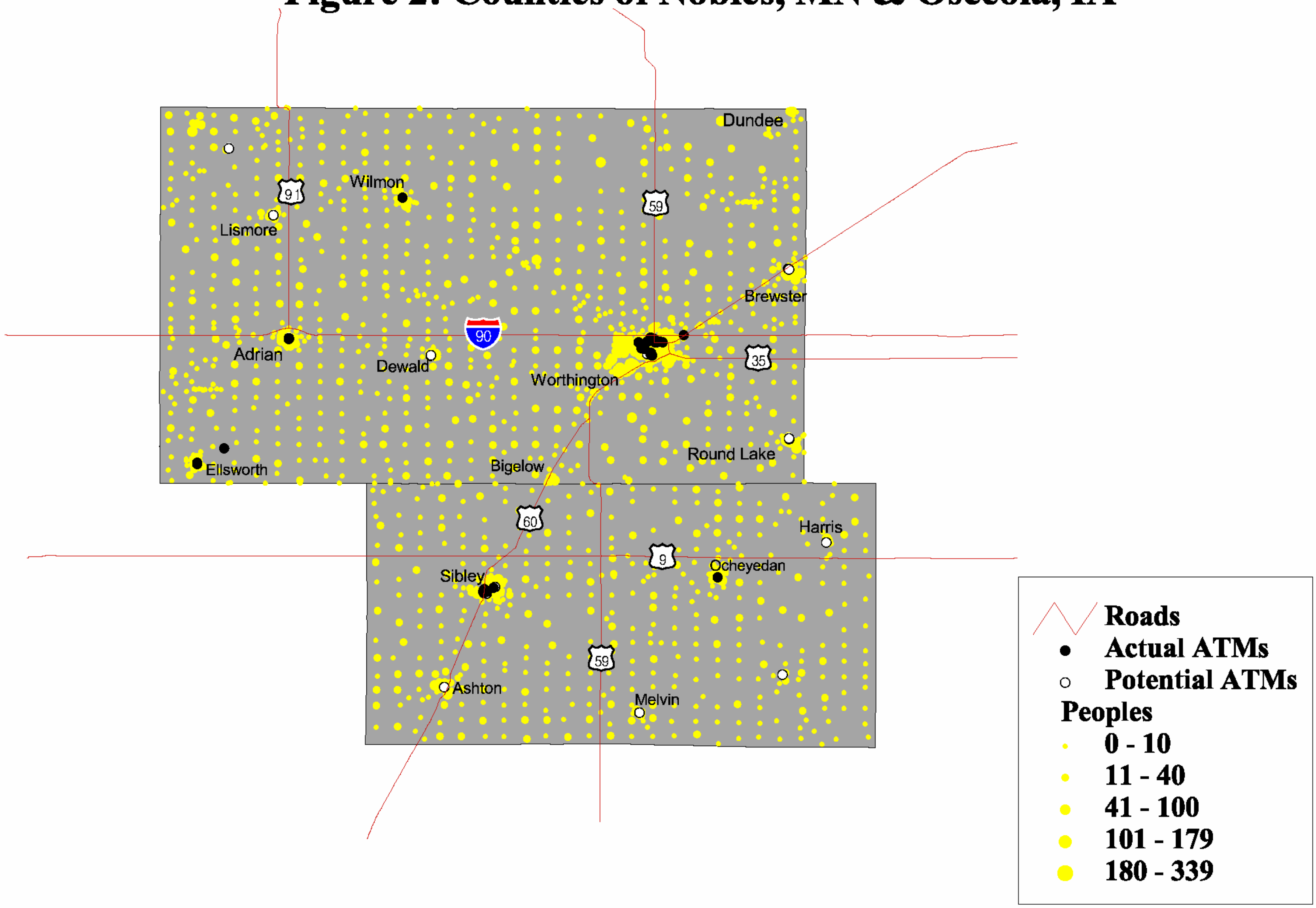


Figure 2: Counties of Nobles, MN & Osceola, IA



Some data issues:

- Need to define which classes of retail establishments are locations for potential ATMs
- We use grocery stores (including convenience stores) and banks
- Could consider other types, e.g. restaurants and movie theatres
- Base results group counties together vertically; others allow entire border region to have same mean fixed costs

Table 1:
Summary statistics of the data by county

	Statistic	Mean	Std. Dev.	Min	Max	N
Iowa	Potential ATM locations	32.6	16.5	14	87	21
	Actual ATMs	18.8	10.9	5	48	21
	ATMs per 1000 consumers	1.13	.347	.458	2.08	21
	Consumers	16,384	8,720	7,267	46,733	21
Minnesota	Potential ATM locations	27.7	8.16	17	42	11
	Actual ATMs	18.3	5.90	10	30	11
	ATMs per 1000 consumers	1.23	.188	.960	1.48	11
	Consumers	15,021	4,910	9,660	22,914	11

Results:

1) Reduced form evidence in data (Table 2)

2) Monte Carlo evidence (Table 3)

2) Base results (Table 4)

3) Robustness checks (Table 5)

4) Policy experiments (Table 6)

Table 2:
Reduced–form determinants of ATM entry

	OLS regressions at county level						
	Iowa	Consumers (1000s)	Potential entry locations	Potential grocer locations	Potential bank locations	Adjusted R^2	Obs
ATMs per 1000 cons.	–.256*** (.073)	–.111*** (.016)	.063*** (.008)			.62	32
Grocer ATMs per cons.	–.207*** (.073)	–.073*** (.017)	.009 (.015)	.050** (.024)		.37	32
	Logit estimation at potential ATM level						
	Iowa	Nearby pot. ATMs	Nearby cons. (1000s)	Near pot ATMs × Iowa	Nearby cons. × Iowa	Log likelihood	Obs.
Entry	–.107 (.250)	–.102 (.094)	4.54** (2.00)	.242** (.110)	–6.0*** (2.28)	–655.2	989

Table 3:
Monte Carlo evidence from simulated equilibrium data

	Method	True parameters used for simulation	Estimated ML	Estimated pseudo–ML, no simulation	Estimated pseudo–ML, simulation	Estimated pseudo–ML, real exog. data
Parameters	Std. dev. un. profit (σ_e)	1.5	1.59 (.321)	1.51 (.331)	1.51 (.319)	1.21 (.518)
	Utility from distance (α)	–.25	–.254 (.069)	–.255 (.067)	–.253 (.066)	–.250 (.133)
	Consumer benefit (δ)	–1	–.831 (.570)	–.931 (.580)	–.942 (.562)	–1.94 (.990)
	Extra bank FC ($\gamma'_{\text{atbank } j}$)	–.5	–.641 (.210)	–.620 (.217)	–.616 (.209)	–.286 (.222)
	Mean fixed cost ($\gamma_{\text{county } j}$)	1	1.15 (.289)	1.10 (.299)	1.09 (.295)	.685 (.676)

Table 4:
Base results

	Parameter	Fixed costs the same Across counties	Fixed cost variation across counties
Estimated from Iowa data	Std. dev. of unobserved profits (σ_e) (Units: \$100)	2.63*** (.763)	1.53*** (.305)
	Utility from distance (α) (Units: kilometers)	–.178 (.156)	–.151** (.070)
	Consumer benefit (δ)	–.696 (1.22)	–.101 (.854)
	Extra fixed cost at bank ($\gamma'_{\text{atbank } j}$)\(Units: \$100)	–.003 (.425)	.057 (.257)
	Mean FC ($\gamma_{\text{county } j}$) Allamakee	.933 (.680)	1.47** (.741)
	Mean FC ($\gamma_{\text{county } j}$) Dickinson		.194 (.539)
	Mean FC ($\gamma_{\text{county } j}$) Emmet		1.34** (.549)
	Mean FC ($\gamma_{\text{county } j}$) Winneshiek		1.47** (.618)
	Mean FC ($\gamma_{\text{county } j}$) Mitchell		4.09*** (.904)
	Log likelihood	–459.0	–437.4
Minnesota data	Utility from price (β)	–1.48*** (.228)	–2.18*** (.182)
	Log likelihood	–192.54	–222.3

Table 5:
Robustness results

	Parameter	Fixed costs the same across counties	Fixed cost variation across counties
Estimated from Iowa data	Std. dev. of unobserved profits (σ_e) (Units: \$100)	3.00*** (1.01)	3.25*** (1.99)
	Utility from distance (α) (Units: kilometers)	–.275 (.316)	–.120** (.198)
	Consumer benefit (δ)	–.910 (1.51)	–1.56 (1.97)
	Extra fixed cost at bank ($\gamma'_{\text{atbank } j}$)\(Units: \$100)	.005 (.483)	n/a
	Mean FC ($\gamma_{\text{county } j}$)	.491 (.946)	.478 (.358)
	Log likelihood	–460.7	–281.8
Minneso ta data	Utility from price (β)	–1.10*** (.195)	
	Log likelihood	–191.9	

Policy experiments:

- We simulate equilibrium entry probability, and consumer and producer surplus under alternate policy regimes: surcharge bans, no surcharge bans, taxes on surcharges and first-best
- We use parameters from Table 4 column 1

Table 6:
Results of counterfactual policy experiments

		Policy: Ban on ATM surcharges	Policy: ATM surcharges allowed	Policy: 20% tax on ATM surcharges	First-best entry and pricing rule
Mean value across counties of:	Cons. surp. /1K people	$446 ($191)	$333 ($170)	$380 ($180)	n/a
	Prod. surp. / 1K people	$441 ($53)	$551 ($76)	$508 ($66)	n/a
	Tot. surp. / 1K people	$887 ($228)	$884 ($234)	$888 ($232)	$1,022 ($239)
	ATMs /1K people	1.12 (.139)	1.27 (1.63)	1.21 (.150)	1.96 (.261)
	Average surcharge	0	$.38 ($.01)	$.30 ($.01)	0
	Volume of transactions	555 (104)	469 (114)	485 (113)	675 (83.8)

Conclusions:

- We specified equilibrium model of ATM utility, costs and entry
- Our specification of utility includes travel distance and price
- We developed a method to estimate the parameters of the model using data on firm and consumer locations
- Estimation procedure is identified by the fact that the State of Iowa fixed surcharge prices of ATMs at zero
- Estimator appears to perform well
- Surcharge ban appears to increase consumer welfare, reduce producer welfare, and leave total welfare roughly the same