Incompatibility and Consumer Demand: Evidence from ATMs

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Abstract

Incompatibility between complementary components of system goods can have substantial effects on consumer welfare. In this paper, we estimate the effects of incompatibility in a classic hardware/software market: ATM cards and machines. Our empirical model allows us to measure the indirect network effect relating ATM availability to willingness to pay for ATM cards (deposit accounts), and also the effects of incompatibility as measured by ATM fees. Our sample contains a relatively discrete move toward incompatibility after 1996, when banks began to impose surcharges on non-customers using their ATM machines. We provide estimates of the partial equilibrium effects of increased incompatibility on consumer welfare, finding that ATM fees *ceteris paribus* reduce the indirect network effect associated with other banks' ATMs. However, a surge in ATM deployment accompanies the shift to surcharging and in many cases completely offsets the reduction in welfare associated with higher fees. This suggests that welfare analyses should consider the interaction between incompatibility and investment in product quality.

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1 Introduction

The last two decades have witnessed a dramatic increase in the importance of markets in which there are *network effects*: complementary relationships in demand for products that may be produced and sold by different firms. These network effects can play an important role in shaping competitive outcomes, and have been a central issue in many high-profile antitrust cases over the last ten years. Of particular interest are the effects of incompatibility between complementary components of network goods sold by different firms, and the relationship between incompatibility and consumer welfare. Theory provides mixed evidence on this question.[1]

In this paper, we estimate the impact of network effects and incompatibility in a classic "hardware/software" industry: Automated Teller Machines (ATMs) and ATM cards. In this market, network effects arise because consumers can use ATM cards and ATMs owned by different banks. This leads to a complementary indirect network effect through which one bank's ATM fleet size affects consumers' willingness to pay for other banks' ATM cards.[2] Furthermore, while consumers may in principle use any bank's ATM card at any other bank's ATM, banks impose fees for such "mix and match" transactions, introducing incompatibility between cards and competitors' machines. There are two such fees. A *surcharge* is paid by the consumer to the owner of the ATM (a bank or independent service operator). The cardholder's own bank may also impose a *foreign fee* for such transactions.

In the limit, these fees can create complete incompatibility between cards and competitors' ATMs, but at lower levels they create partial incompatibility. In our empirical work, we focus primarily on surcharging as a metric of incompatibility, though we also control for the existence of foreign fees. This emphasis stems from the nature of our data, which cover a period that exhibits a regime change in surcharging; until 1996 the largest networks barred banks from imposing surcharges, while after 1996 surcharges became widespread.[3] This represents a relatively discrete shift toward incompatibility. Foreign fees, on the other hand, remain roughly constant across and within banks throughout our sample period.

The key empirical question that we examine is whether greater incompatibility leaves consumers better or worse off. While incompatibility *ceteris paribus* leaves consumers worse off because it

[1] See Katz and Shapiro (1994) for a summary of the literature and its key points.

[2] "Direct" network effects occur when an adopter generates benefits for other users of the same product, as in a communications network. For a discussion of the distinction and its theoretical relevance, see Katz and Shapiro (1994).

[3] Sixteen states overrode the ban prior to 1997; we account for this in the empirical work below. See Prager (2001) for an examination of surcharging prior to 1997.

reduces their mix and match options, it also may be associated with other welfare changes. For example, incompatibility may change firms' incentives to invest in the quality of their network components; this incentive may counterbalance the harmful effects of incompatibility. On balance, the cumulative effect on consumer welfare may be positive or negative.[4]

In general, it is difficult to empirically estimate the effects of incompatibility. Beyond the classic problems involved in inferring welfare changes, there are unique problems associated with estimating welfare effects of incompatibility in network markets. Very few markets display variation in compatibility over time, meaning that data regarding changes in compatibility are scarce. Moreover, because network effects operate through multiple components of a system, a complete welfare analysis requires data on prices and characteristics for each component of the network.

Our data are well-suited for such an analysis. We conduct our empirical work using a data set containing ATM-related characteristics for banks operating in different local markets throughout the United States. Our data cover the period 1994-1999, containing roughly ten thousand bank/county/year observations. Each observation contains information regarding the bank's ATMs and ATM fees, as well as the number of competitors' ATMs available to customers and their fees. It also contains information regarding deposit account (ATM card) prices and market shares, as well as characteristics associated with these accounts. Thus, we possess panel data on prices, quantities and characteristics for both components of the network good, as well as a measure of incompatibility.

The empirical approach involves estimating a structural model of consumer demand for deposit accounts (ATM cards) as a function of deposit account prices, ATM density and other bank characteristics. The model allows us to estimate consumers' willingness to pay for deposit accounts, and the influence of ATMs on willingness to pay. It also allows us to estimate the indirect network effect: the relationship between willingness to pay for an account and competitors' ATM fleet size. We test whether incompatibility reduces the strength of the indirect network effect, by allowing competitors' surcharging to reduce willingness to pay deriving from access to competitors' ATMs.

The estimated parameters from this model provide the basis for our welfare analysis. The first component of the welfare effect is the partial equilibrium reduction in consumer welfare resulting from the shift toward incompatibility. We also provide a fuller estimate that incorporates changes in ATM deployment—both for a given bank's own ATMs and its competitors' ATMs. Our results suggest that incompatibility *ceteris paribus* harms consumers during our sample. Surcharging

[4]Incompatibility may also change the intensity of price competition. While we plan to address this issue in future work, our current study focuses solely on demand-side effects.

significantly reduces the indirect network effect conferred by competitors' ATMs; the parameter estimates imply that consumer welfare is ten percent lower under surcharging. However, ATM deployment increases following surcharging, providing benefits to customers that in some cases completely offset the reduction in welfare associated with incompatibility. Roughly stated, the net effects on welfare are more likely to be positive in urban areas, and more likely to be negative in rural areas.

We also estimate split sample specifications that allow the demand parameters to vary by local market population density. We find that the network effects associated with ATMs and cards are much stronger in areas with high population density. This is consistent with the idea that in areas with high travel costs, ATM access is more valuable to consumers. Using the parameters from the split samples, we find that welfare changes in low density markets are essentially zero, while welfare changes in high-density areas average roughly fourteen percent.

To our knowledge, ours is the first empirical study to examine changes in incompatibility in a market characterized by indirect network effects.[5] To date, most research has examined the value of compatibility across different products in markets with direct network effects.[6] It also has focused on instances where compatibility between products remains fixed over time, relying on cross-sectional variation in compatibility for identification.[7] Our work does relate to a developing literature establishing empirical relationships in markets with indirect network effects, but this work examines markets in which compatibility between different systems is fixed.[8] It also complements existing literature examining ATM markets, although that literature does not focus on incompatibility *per se*.[9]

[5]An exception is Greenstein (1994), who finds that mainframe buyers prefer to upgrade to compatible systems, a result suggesting that compatibility between past and future hardware is important.

[6]Gandal (1994, 1995) and Brynjolfsson and Kemerer (1996) find that computer spreadsheets compatible with the Lotus system commanded higher prices during the early 1990s.

[7]The analyses in Gandal (1994, 1995) and Brynjolfsson and Kemerer (1996) do not separate within-firm from cross-sectional effects of compatibility. The datasets are panels, but too small to allow the examination of within-firm variation.

[8]Gandal, Greenstein and Salant (1999) study the link between operating system values and software availability in the early days of the microcomputer market. They find evidence supporting the existence of complementary feedback between hardware and software availability. More recent work by Gandal, Kende and Rob (2002) seeks to establish a positive feedback link between adoption of Compact Disks (CDs) and CD players. Rysman (2000) provides evidence supporting the existence of complementary demand relationships in a two-sided platform market (yellow page directories). More recent work by Shankar and Bayus (2002), Nair, Chintagunta and Dube (2003) and Ohashi (2003) also applies structural econometric techniques to test for the existence of network effects.

[9]Hannan et al. (2003) examine surcharging although they do link surcharging to deposit account pricing. Prager

2 ATMs, ATM Cards and ATM Fees

ATMs allow bank customers to perform financial transactions electronically. ATM development stemmed from banks' desire to cut costs by automating tasks performed by bank tellers. While ATMs can in principle perform more complex transactions such as deposits or loan payments, the most common transaction is a cash withdrawal.[10] Banks locate or *deploy* ATMs both "on-premise" at branches, and "off-premise" at other locations likely to generate significant transaction volume.[11] Independent Service Operators (ISOs) also deploy ATMs, typically in lower-volume locations such as convenience stores, restaurants and bars.[12]

Banks grant consumers access to their ATMs by providing ATM cards with checking (demand deposit) accounts. The deposit account also carries other services, such as check-writing and direct deposit for paychecks. Banks are differentiated both horizontally through geography, and vertically through service quality. Survey evidence suggests that the most important account features in determining customer attraction and retention are service quality and ATM/branch location.[13] Customers also may value purchasing other financial services such as loans or brokerage services from their depository institution; these represent complementary service offerings associated with the account.

Customers pay both implicit and explicit prices on deposit accounts. The implicit cost is the opportunity cost of holding cash in a non-interest bearing account, or earning an interest rate below the risk-free rate if the checking account pays interest. Explicit costs may include a monthly service charge, fees associated with transactions (such as check-writing), and penalty fees such as

(2001) tests whether small banks lost market share in states that allowed surcharges prior to 1996; this is implicitly a test of whether incompatibility favored banks with high-quality ATM fleets, although she does not pose the question in those terms. Hannan and McDowell (1990) find that markets in which large banks adopted ATMs became more concentrated during the 1980s, although they do not discuss their finding in terms of network economics. Saloner and Shepard (1995) examine the diffusion of ATM machines from 1972-1979 and find that adoption occurred earliest for firms with many branches and deposits, a result they interpret as consistent with the existence of indirect network effects in demand. Earlier work by Hannan and McDowell (1984a, 1984b) also examines the causes of ATM adoption but does not test for network effects.

[10] Dove Consulting (1999, 2002) finds that in both 1999 and 2002, roughly eighty percent of ATM transactions were cash withdrawals. Deposits and inquiries comprise roughly ten percent each.

[11] Monthly costs of ATMs average over $1000 for high-end machines, and may be as low as $500 for low-end machines offering fewer features and using cheaper telecommunications. Rental expenses for off-premise ATM deployment may add $200/month to this figure.

[12] See Dove Consulting (1999, 2002) for more details.

[13] See Stavins (1999) and Kiser (2003) for discussions of account characteristics valued by banking customers.

NSF (insufficient funds) fees. Banks often offer customers a menu of options, trading lower explicit fees or interest payments for higher minimum balances. The menus are usually determined at the bank level, and identical across all branches for that bank.[14] While total account costs for any one customer may vary in principle depending on their pricing plan and balances, available survey evidence suggests that these costs are similar for accounts with or without minimum balances, averaging roughly $144 per year.[15]

Consumers typically pay no per-transaction fees for ATM transactions made at their own bank's machines. They can also use other banks' ATMs to make *foreign* transactions, because during the 1980s most banks joined "shared networks" that allow consumers to use their card at any ATM owned by a bank in the network. These ATM networks, which are often joint ventures organized by member banks, provide switching services for each foreign transaction made on a member bank's ATM by another member bank's customer. The networks jointly establish a fixed subscription fee for each member bank in the network, a per-transaction switch fee paid by the cardholder's bank to the network, and a per-transaction interchange fee paid by the cardholder's bank to the ATM owner.[16] By the mid-1990s, shared networks had expanded to the point that an ATM card would function at nearly any ATM in the country.[17]

A foreign transaction may generate a *foreign fee* paid to the consumer's home bank, and a *surcharge* paid to the owner of the ATM. Foreign fees exist throughout our sample, while surcharges are a more recent phenomenon. Prior to 1996, the major ATM networks (PLUS and Cirrus) prohibited banks from imposing surcharges. The major networks ostensibly prohibited surcharging in an attempt to build consumer acceptance of foreign transactions. The prohibition on surcharging was challenged by both banks and state legislatures; banks claimed that surcharging would enable them to deploy ATMs in lower-volume locations, while states viewed the ban as a potentially illegal vertical restraint. Prior to 1996, sixteen states overrode the surcharge bans. Furthermore, antitrust actions regarding the surcharge ban were being considered by the Department of Justice. Facing

[14] Radecki (1998) provides evidence in favor of this point.

[15] See Stavins (1999) for details.

[16] Data from the Card Industry Directory show that network subscription fees vary substantially, with larger national networks charging higher fees (as much as $25,000 for membership and $500 monthly). Interchange fees range from $0.30-$0.60 per transaction during our sample, and switch fees range from $0.02-$0.12. Many networks apply some sort of volume discount to their pricing.

[17] Currently it is most common for a bank to subscribe to one of the major national networks, and one or two regional networks (which have priority in switching transactions relative to the national networks). It is also quite common for banks to subscribe to the VISA or Mastercard networks, allowing their customers to use their ATM cards to perform signature-based "offline" debit transactions on those networks.

this pressure, the leading networks eliminated the ban. From 1997-1999, most banks adopted surcharges, and they are currently nearly universal. Both foreign fees and surcharges are set at the bank level; it is uncommon for a bank to set different fees on different machines.[18] It is also uncommon for banks to charge different fees in different local markets.

Table I shows summary statistics regarding ATM fees, deployment and transaction volume during our sample period 1994-1999. The data illustrate that while foreign fees remain roughly constant throughout our sample period, surcharging becomes much more prevalent after its inception in 1996.[19] Concurrent with the advent of surcharging is an increase in ATM deployment; the average annual growth rate is under fourteen percent from 1993-1996, and nearly eighteen percent after 1996. Transaction volume holds steady after the advent of surcharging, after growing rapidly prior to 1996. This leads to fewer transactions per ATM, a pattern consistent with the notion that the break-even number of transactions per ATM is much lower if foreign transactions generate surcharge revenue.[20]

2.1 The Network Economics of ATMs and ATM Cards

In the language of the literature on network economics, ATM cards and machines are a "hardware/software" system.[21] Consumers purchase "hardware" in the form of an ATM card by choosing a bank and establishing an account. ATMs are "software" that allow consumers to assemble a composite good—a financial transaction that is usually a cash withdrawal. This "mix and match" construction of goods is a common feature of emerging technologies, and is analogous to that involved in consumers' matching of computer hardware and software, operating systems and spreadsheets, different components of audio/visual systems, and a variety of other products. In ATM markets,

[18] Our data from the Card Industry Directory allow banks to list a range of fees. Fewer than ten percent do so. Additionally the Bank Rate Monitor web site, www.bankrate.com, lists ATM fees by geographical region for multi-region banks. There is little evidence from this source that banks charge different fees on ATMs in different locations.

[19] These data show that some banks imposed surcharges in 1996; these banks either operated in states that overrode the surcharge ban, or subscribed to smaller networks that did not adhere to the ban. Unfortunately, we do not possess data in our primary sample on surcharging prior to 1997.

[20] This difference is dramatic. A study by Dove Consulting estimates the monthly accounting costs of maintaining an ATM at roughly $1200. If interchange ($0.40 per transaction) is the only source of ATM revenue, the break-even number of foreign transactions per month is 3000. If interchange plus surcharging yields revenue of $1.90 per foreign transaction, the break-even monthly number of foreign transactions falls to 631.

[21] See Katz and Shapiro (1994) for a survey of this literature. Economides and Salop (1992) present a theoretical model of hardware/software competition using ATMs as an example.

as in many of the aforementioned examples, firms produce both hardware and software, and offer their customers bundles containing both. Thus, a customer establishing an account receives both an ATM card and free access to that bank's ATMs. This suggests that for the purpose of understanding ATM markets, the most relevant models of competition in hardware/software markets are those in which integrated firms sell both hardware and software.[22] Our focus in this paper is on estimating consumer welfare. We therefore are concerned primarily with the implications of network effects for consumers' willingness to pay for components of the system—which in our case is the hardware/software bundle offered by banks. Our discussion takes firms' strategic behavior regarding pricing, incompatibility and quality as given, and focuses on the effects of changes in these factors on consumers. This parallels our empirical approach, which uses variation in incompatibility to estimate changes in consumer welfare.

We would expect a consumer's willingness to pay for an account and associated ATM services to depend on the characteristics of the account—service quality, for example, as well as any complementary services offered with the account. One (internalized) indirect network effect in the bundle is that willingness to pay should also depend on the bank's own ATMs. Consumer incur travel costs to use ATMs; therefore, a greater number of local ATMs reduces travel costs and makes an account more attractive. It also means that if consumers value accounts based on which bank has the ATMs closest to "home," more consumers will be closer to an ATM of that bank. The second indirect network effect on willingness to pay is that competitors' ATMs also provide benefits, because ATMs operate on shared networks. While consumers may prefer to use an ATM operated by their own bank (even absent fees, they can perform a wider array of transactions on their own ATMs), they also should value occasional access to other banks' ATMs.

2.2 ATM Fees as Incompatibility

In hardware/software markets, the compatibility issue revolves around whether Firm A's hardware will function with Firm B's software, and vice versa. The most general result of these models is that incompatibility reduces consumers' willingness to pay, *ceteris paribus*. The strength of this effect depends on the degree to which consumers want to mix and match hardware and software from different sellers. If demand for such transactions is zero, incompatibility leaves consumers

[22]Chou and Shy (1990), Church and Gandal (1996), and Matutes and Regibeau (1988) consider cases where hardware and software are sold by integrated firms. Economides and Salop (1992) provide a comparison of market structures characterized by different forms of integration and ownership among component (hardware and software) producers. Matutes and Regibeau (1992) examine a case where firms produce both hardware and software, and may bundle them together.

unaffected, but if demand for mix and match transactions is high, incompatibility reduces aggregate willingness to pay. These effects may vary by firm; firms with high demand for mix and match transactions will experience a larger reduction in willingness to pay.

ATM surcharges create incompatibility by increasing the cost of access to other banks' ATMs. While surcharges do not render competitors' ATMs fully incompatible, they impose an incremental expense for foreign ATM use. In the language of network economics, this expense is most analogous to an "adaptor fee" paid by software users to achieve compatibility with potentially incompatible hardware.[23] This effect should weaken the relationship between willingness to pay for an ATM card (account) and the number of accessible competitors' ATMs.

2.3 Incompatibility and ATM Deployment

Ceteris paribus, we would expect incompatibility to leave consumers worse off, but in our case it is important to consider the other influences on consumer welfare that might have changed after 1996. One important influence is ATM deployment. Anecdotally, it appears that ATM deployment accelerated after 1996; using the data from Table I reveals that within our sample, the annual growth rate of ATMs increased from roughly fourteen percent to over eighteen percent after 1996. A prominent explanation for this shift is that incompatibility strengthened incentives to invest in product quality, because ATM owners could extract rents associated with their ATM fleets. Another explanation for increased ATM deployment is that firms attempted to leverage competitive advantage in ATM fleets into the deposit account market.[24] Within the context of network economics, one can interpret this as analogous to attempts by firms to leverage market power in either hardware or software into a complementary market; incentives for doing so are stronger under incompatibility.[25] In ATM markets, small banks have alleged that large banks use ATM fees as a device to attract market share. High surcharges, the argument goes, induce customers with high demand for foreign transactions to migrate their accounts from banks with small ATM fleets to banks with large ATM fleets.

In order to fully assess the welfare effects of incompatibility, then, we need to estimate not only the reduction in utility stemming directly from incompatibility, but also any changes in ATM

[23] See Farrell and Saloner (1992) for a model of adaptors in a hardware/software market.

[24] These incentives are the primary focus of the theoretical models of ATM pricing and deployment in Massoud and Bernhardt (2002a, 2002b).

[25] See Church and Gandal (1996, 2000) and Carlton and Waldman (2002) for analyses of incompatibility, leveraging and foreclosure in system markets.

deployment associated with the shift toward incompatibility. From a theoretical perspective it is not clear which effect will dominate. Much of the existing literature on incompatibility does not model firms' decisions regarding product quality or characteristics.[26] A further complication, and one that we do not fully model, is that incompatibility may change the intensity of competition. Here again theory is ambiguous; models of competition in mix and match markets find that incompatibility may either intensify or weaken price competition.[27] Despite this theoretical ambiguity, our intuition tells us that in ATM markets the advent of surcharging would probably weaken price competition.[28] Without ATM fees of any sort, ATM fleet size is not a source of horizontal or vertical product differentiation. As fees rise, the degree of differentiation also rises, which we would expect to weaken business-stealing opportunities. Our empirical work below should control for such shifts in competitive behavior, although we can not identify the size of their effects.

3 Modeling

In order to measure the effects of incompatibility on consumer welfare, we estimate a structural demand system for deposit account services and ATM usage. This follows techniques developed by Berry, Levinsohn and Pakes (1995), building on Lancaster (1966). The essence of the empirical approach is to estimate the relationship between consumer utility and product characteristics; specific products are modeled as bundles of characteristics. Under specific assumptions regarding the functional form of preferences on observed and unobserved characteristics, there is a structural relationship between aggregate firm-level market shares and the parameters of consumers' indirect utility functions. This approach is more parsimonious than traditional demand system estimation, as it reduces the large matrix of own- and cross-price elasticities to a smaller matrix of coefficients associated with product characteristics.

[26] Classic papers on "mix and match" competition such as Matutes and Regibeau (1988) and Economides (1989) assume that product characteristics are fixed. Einhorn (1992) models the effect of quality differences across component producers, but assumes that such differences are exogenous.

[27] The discussion in Katz and Shapiro (1994) mentions instances in which compatibility might intensify price competition. Matutes and Regibeau (1988), Economides (1989) and Einhorn (1992) all find that compatibility relaxes price competition. Katz and Shapiro (1986) find that in a dynamic setting, compatibility has different effects on competition at different points in the product life cycle.

[28] We find evidence consistent with this view in Knittel and Stango (2003).

3.1 Consumer Behavior

In our econometric framework, the fundamental consumer choice is the establishment of a demand deposit (checking) account relationship with a bank. Consumers choose from the set of banks within their county in order to maximize indirect utility.[29] Consumer i's utility for bank j in county k in year t is a function of the price for a deposit account p_{jt}, bank j's observable deposit account characteristics x_{jkt} in county k in year t, the access to ATMs N_{jkt} provided by obtaining an account, the bank's unobservable characteristics ξ_j, county level unobservable characteristics ξ_k, bank/county unobservable characteristics ξ_{jk}, unobservable year-specific characteristics ξ_t and a mean zero term ϵ_{ijkt} capturing unobserved consumer heterogeneity.[30] This yields the following specification:

$$u_{ikjt} = \alpha_i p_{jt} + x_{jkt}\beta_i + N_{jkt} + \xi_{jk} + \xi_t + \epsilon_{ikjt} \tag{1}$$

While in practice the vector of marginal utility coefficients (α_i, β_i) varies by consumer, in this instance we restrict the coefficients to be constant across consumers. By omitting income from the utility function, we are assuming that there are negligible income effects when establishing a depository account. Given the low share of consumer income devoted to purchasing checking account services, we feel this is reasonable.

3.2 Deriving the Estimating Equation

As shown by Berry (1994), if ϵ_{ikjt} follows an extreme value distribution one can integrate the individual utilities to obtain an estimating equation that provides a structural relationship between the utility parameters and market shares for each firm. This yields the following equation:

$$\ln(s_{jkt}) = \alpha p_{jt} + x_{jkt}\beta + N_{jkt} + \xi_{jk} + \xi_t + \Delta\xi_{jkt} \tag{2}$$

This is a useful transformation in our case, because while we do not observe individual consumer choices, we do possess bank/county/year observations on market share, prices and other explanatory

[29] Using counties to approximate local markets is common in the banking literature. Some recent work (e.g., Radecki [1998]) argues that geographic banking markets have expanded. However, we feel that while this may be true for products such as loans, it is much less likely to be true for ATM-related services. In fact, we use the county as the market even in MSAs, rather than treating the MSA as the market. In practice this has no effect on our results.

[30] While in principle there are separate bank effects ξ_j, county effects ξ_k and bank/county effects ξ_{jk}, in practice we nest them within ξ_{jk}.

variables of interest. Note that the consumer-specific heterogeneity has been "integrated out" here, and replaced by the bank/county/year specific term $\Delta\xi_{jkt}$ capturing unobserved quality.

While econometrically tractable, the specification of utility that leads to this estimating equation is quite restrictive.[31] A significant limitation is that a proportional increase in all bank prices will not reduce demand for banking services. A common way to guarantee that banks lose market share when prices rise involves choosing an "outside good" to which consumers can switch given an increase in prices by all banks. In our case, we not only observe deposits for banks in each county, but also observe deposits for credit unions; these institutions are imperfect substitutes for banks and are the product to which consumers might conceivably switch given higher bank prices.[32] We therefore treat banks as the "inside good" and credit unions as the outside good.

Another way of enriching the model is to assume that consumers make a two-stage decision, in which they first decide whether to establish an account at a credit union or at a bank. Given that choice, they make their second stage decision regarding with which institution to establish an account. This allows for more intuitive substitution patterns, in which a consumer switching away from a bank is more likely to switch to another bank than to a credit union. In a manner similar to that outlined above, one can begin with a general specification in which consumers have heterogeneous preferences for remaining in each "nest." These are also integrated out under specific assumptions regarding the form of the heterogeneity. As Berry (1994) shows, this leads to the following nested logit estimating equation:

$$\ln(s_{jkt}) - \ln(s_{okt}) = \alpha p_{jt} + x_{jkt}\beta + N_{jkt} + \sigma_t \ln\left(\bar{s}_{j|g}\right) + \xi_{jk} + \xi_t + \Delta\xi_{jkt} \tag{3}$$

The term s_{okt} is the market share of the outside good, while $\bar{s}_{j|g}$ is bank j's share of the inside good. The term σ_t represents the correlation between consumer choices within each nest; higher values of σ_t reflect a higher likelihood that a consumer switching away from one bank will choose another bank rather than a credit union. Letting the term vary by year allows the substitutability between the inside and outside goods to change over time.

[31] See Nevo (2000) for a discussion of these issues, and some improvements to the model we use here.

[32] To be more precise, we treat banks and thrift institutions as the inside good. We have also estimated the model treating banks as the inside good, and thrifts/credit unions as the outside good. This has little effect on the results.

3.3 Measuring Market Share

We use data from the FDIC *Summary of Deposits* database to obtain the total deposits held by each bank in each county of operation during our sample period.[33] Similar data from the National Credit Union Administration (NCUA) yield deposit data for credit unions, which we use to calculate the share of the outside good.[34] In our sample, the share of deposits held by the inside good falls slightly over time as credit unions gain market share. Anecdotally, it also appears that the substitutability of credit unions and banks grew over time as well, because credit unions have expanded their service offerings to more closely match those of banks.

One issue associated with our dependent variable is that it is based on total deposits held by each bank. Total deposits include not only checking (deposit) account balances, but also savings and other time deposits such as money markets and CDs. Thus, this total market share may measure checking deposit market share with error. In principle, this can present a problem in our framework, even if the measurement error is of a form that is innocuous in more standard linear regressions.[35] In practice, however, there is little evidence that this error is significant.[36]

3.4 Deposit Account Prices

We take pricing data on deposit accounts from the FDIC Reports of Condition and Income, or Call Reports. These data are available at the card issuer (bank) level. The variable listed in the Call Reports shows annual income from fees associated with deposit accounts. The primary component of such revenue is income from monthly service charges on transaction accounts.[37] It also includes foreign fee income paid by its customers stemming from the use of other issuers' ATMs, and a variety of other fees such as NSF fees for bounced checks and other penalty fees on accounts. To calculate a normalized price for each bank, we divide this value by the end-of-year dollar value of

[33] The SOD also contains deposit data for thrifts. While we use thrift deposit data in calculating market shares, we can not include observations for thrifts in our sample because we do not possess prices or other data for them.

[34] The mean outside good share is roughly twelve percent in our sample; the interquartile range is [0.01, 0.16].

[35] See Berry (1994) for a discussion.

[36] At the bank level, the correlation between total deposits and demand deposits is 0.98.

[37] This variable also includes income on other types of deposit accounts that do not carry ATM card access, introducing measurement error. However, these other types of accounts (such as savings) typically have lower fees than checking accounts. We examine within-bank variation in these fees, meaning that our results below will only be biased if within-bank variation in other fees is correlated with our variables of interest (e.g., ATMs). Most importantly, we use an instrumental variable approach that controls for the measurement error in price, as well as the endogeneity of price.

deposits held in transaction accounts.[38] This price measure therefore represents the average revenue per dollar (per year) of transaction account balances. While it undoubtedly averages over the many different fees and fee schedules offered by each bank, this price measure is highly correlated with annual price measures using finer data.[39]

This measure omits the additional opportunity cost of holding deposits in checking.[40] While this opportunity cost surely varies across customers, Radecki (1999) suggests using the federal funds rate as an approximation of forgone interest income for demand deposit balances. We therefore add the average annual fed funds rate to each bank's price.[41] While this does not affect any of our coefficient estimates because they rely on within-bank variation in prices over time, it does provide a useful benchmark for comparing our price measure to others. As a point of comparison, we find that our raw price measure averages roughly \$0.01 per dollar of transaction balances, while the cost of funds averages roughly \$0.05. The typical checking account has average balances of \$1600, implying an annual cost of \$96 for the typical checking account; this figure is in line with other estimates in the banking literature.

Of course, the discussion above should make clear that our price variable is subject to measurement error. However, if this measurement error is fairly constant over time it is not an issue because we use within-bank variation to estimate the model.[42] Additionally, our instrumental variable procedure outlined below should account for measurement error that varies over time.

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[38] We have also used an alternative measure that divides deposit fee income by the dollar value of deposits. This is the variable used by Dick (2002) in her study of consumer welfare in deposit markets. Our results using this measure are nearly identical to those shown below.

[39] Stavins (1999) regresses the fee variable used in our price on actual fee data from surveys (such as minimum balance requirements, monthly fees etc.) and finds that the explanatory variables explain over eighty percent of the variation in fee income.

[40] Radecki (1999) suggests using the federal funds rate as a measure of forgone interest income for demand deposit balances.

[41] We would expect there to be considerable consumer-level heterogeneity in the opportunity cost of funds. Consumers carrying credit card balances, for example, would have high costs. This might affect the bank-level cost of funds if consumers are not uniformly allocated across banks. However, our instruments (in particular those measuring the riskiness of a bank's customer base) should capture at least some of this variation.

[42] Large banks tend to pay lower interest than smaller banks. This may refect quality differences or market power. If savings rate differences stem from market power and consumers face switching costs, we will slightly overstate the price difference between large and small banks using our fee income variable.

3.5 Specifying the Benefits of ATMs

The access to ATMs associated with an account N_{jkt} will depend on bank j's ATM deployment in the local market. It will also depend on the network effects conferred by other banks' ATMs, and the compatibility of those other ATMs. We model this access using the following specification:

$$N_{jkt} = b_1 \ln(OwnATMs_{jkt}) + [b_2 + b_3 E(s_{-j,kt})] \ln(CompetATMs_{jkt}) \tag{4}$$

The first term b_1 measures the value of bank j's ATMs in the local market.[43] We measure the ATM variable in logs to capture the declining marginal value of ATMs; the incremental effect of an additional ATM falls with more ATMs in the market, growing negligible as the market becomes saturated.

The second term estimates the value of the indirect network effect associated with the presence of competitors' ATMs. This value is represented by the term $[b_2 + b_3 E(s_{-j,kt})]$, where b_2 represents the value of a competitors' ATM with full compatibility (zero surcharges), and b_3 represents the reduction in value from competitors' ATMs caused by surcharges. This gives the following specification:

$$\begin{aligned} \ln(s_{jkt}) - \ln(s_{okt}) &= \alpha p_{jt} + x_{jkt}\beta + b_1 \ln(OwnATMs_{jkt}) \\ &\quad + [b_2 + b_3 E(s_{-j,kt})] \ln(CompetATMs_{jkt}) \\ &\quad + \sigma_t \ln \bar{s}_{j|g} + \xi_{jk} + \xi_t + \Delta\xi_{jkt} \end{aligned} \tag{5}$$

One methodological issue associated with this specification is that it includes the impact of foreign fees only in the price term p_{jt}. While in one sense foreign fees are a part of the consumer's expected costs associated with an account, it is also true that foreign fees create incompatibility. While we can not separate the share of p_{jt} driven by foreign fee revenue, we do estimate specifications that allow a bank's foreign fees f_{jt} to affect the value of competitors' ATMs:

$$\begin{aligned} \ln(s_{jkt}) - \ln(s_{okt}) &= \alpha p_{jt} + x_{jkt}\beta + b_1 \ln(OwnATMs_{jkt}) \\ &\quad + [b_2 + b_3 (f_{jt} + E(s_{-j,kt}))] \ln(CompetATMs_{jkt}) \\ &\quad + \sigma_t \ln \bar{s}_{j|g} + \xi_{jk} + \xi_t + \Delta\xi_{jkt} \end{aligned} \tag{6}$$

[43] One might imagine that a density measure such as ln(ATMs per square mile) might be appropriate. Our definition is equivalent with fixed county effects and our log specification, because the square mileage of counties does not change over time.

Another issue is that while we only observe surcharges in 1997 and beyond, some banks did begin to surcharge prior to that point because they operated in a state that had overridden the ban. We do know which states overrode the ban, allowing us to estimate a specification using a simple dummy variable to measure the transition to surcharging:

$$
\begin{aligned}
\ln(s_{jkt}) - \ln(s_{okt}) &= \alpha p_{jt} + x_{jkt}\beta + b_1 \ln(OwnATMs_{jkt}) \\
&\quad + [b_2 +_{3} b_3 (f_{jt} + E(s_{-j,kt})) + b_4 I (k \in S_t \ \& \ t < 1996)] \ln(CompetATMs_{jkt}) \\
&\quad + \sigma_t \ln \ \bar{s}_{j|g} \ + \xi_{jk} + \xi_t + \Delta\xi_{jkt}
\end{aligned} \tag{7}
$$

where S_t is the set of state that overrode the surcharge bank. Thus, b_4 represents the reduction in the indirect network effect associated with competitors' ATMs in the states that overrode the ban prior to 1996, while b_3 measures the effect of incompatibility after 1996. In the main results section below, we report estimates from equation (7). We also report results using the other measures of incompatibility in appendix Table A3; the results are qualitatively very similar, although the coefficient on incompatibility is estimated more precisely in our preferred specification.

3.6 ATM-Related Data and Measurement Issues

While we possess data on market shares and deposits for the population of banks, we only observe data on ATM fees and deployment for the 300 largest ATM card issuers. While these issuers collectively hold a large share of the total market (for cards or machines), we do not observe such data for smaller issuers. The primary effect of this limitation is to reduce our useable sample size, as we only include in our estimating sample those observations for which we observe both ATM fees and ATM deployment.

Another issue with our ATM data is that while we observe each issuer's total ATM deployment, we do not observe the allocation of that deployment across counties. This is not a problem for single-county issuers, which represent twenty-five percent of our observations. For the other issuers, we assume that banks allocate ATMs across counties in proportion to their branches (which we observe without error from the Summary of Deposits). That is, we use:

$$
OwnATMs^*_{jkt} = \frac{Branch_{jkt}}{Branch_{jt}} OwnATMs_{jt} \tag{8}
$$

This introduces error into our measure of $OwnATMs_{jkt}$. To the extent that the measurement error is constant for a particular bank/county over time, our fixed effects will control for it. However, it is possible that there is time-varying bank/county measurement error. As is well-known, measurement error in an independent variable leads to attenuation bias, which brings the absolute value of the estimated coefficients closer to zero. A number of methods for correcting attenuation bias exist.[44] Below we discuss our method and some robustness checks of that method.

Competitors' ATMs also are measured with error, because we do not observe ATM deployment for every bank in each county.[45] We rely on the information we do have regarding competitors' branches to estimate competitors' ATMs, using a regression-based method. We have experimented with several estimation methods, all of which yield similar results, in part because the ATM deployment of smaller issuers is fairly easy to predict; almost all smaller issuers deploy roughly one ATM per branch, with deployment growing slightly over time.[46] In the results shown here, we use a regression-based imputation method that uses data from our observed issuers to fit ATM deployment for other issuers in local markets.[47]

We also face measurement error in constructing a measure of competitors' ATM fees. We use a regression-based method for imputing expected competitors' surcharges.[48] Again, we have experimented with alternative methods of estimating competitors' fees, with little effect on the results. The shift to surcharging is fairly discrete, meaning that small differences in a prediction of competitors' surcharges are swamped by the change occurring between 1996 and 1998. In fact,

[44]See Fuller (1987) for an exposition of the problem and comprehensive treatment of the literature up to that point. One line of research proposes techniques when the "reliability ratio" or some other independently available index of the degree of error is available; see Fuller (1987) for examples and solutions. In the absence of such information, Griliches and Hausman (1986) and Biorn (2002) propose instrumental variable techniques appropriate for use with panel data, although their techniques involve differencing which would substantially reduce our sample size. Lewbel (1997) and Dagenais and Dagenais (1997) suggests using higher moments of the observed variables as instruments; we discuss and apply this technique below.

[45]On average, the banks for which we observe ATM-related data collectively hold forty-seven percent of deposits in the county. Their share of ATMs in that county is almost surely higher.

[46]For more detail on differences between large and small issuers, see Knittel and Stango (2003)

[47]In order to estimate the number of ATMs deployed by other institutions, we estimate a within-sample regression of ATMs on branches, year dummies and year/branch interaction terms. To control for the fact that larger institutions have a greater ratio of ATMs to branches, we allow issuer size (in deposits) to affect branches per ATM. We also allow branches per ATM to vary based on whether the issuer is located in an MSA or non-MSA county. We then construct fitted values of ATMs for each institution for which we do not have ATM data. We have experimented with a number of alternative specifications of this model, with essentially no change in the results.

[48]We first estimate the within-sample probability of surcharging and surcharge level (conditional on surcharging) based on issuer size, year effects, MSA dummies and interactions between these variables. We then predict the expected surcharge (probability of surcharging multipled by expected surcharge) for each competing bank. The expected competitors' surcharge is an average of these and observed surcharges over all competitors in the local market, weighted by each competitors' share of branches in the local market.

using a simple dummy variable indicating whether competitors can impose surcharges yields results very similar to those shown below.

We are left with three independent variables that may be measured with error, meaning that our estimating equation is:

$$
\begin{aligned}
\ln(s_{jkt}) - \ln(s_{okt}) = {} & \alpha p_{jt} + x_{jkt}\beta + b_1 \ln\left(OwnATMs^*_{jkt}\right) \\
& + \left[b_2 + b_3\left(f_{jt} + E\left(s^*_{-j,kt}\right)\right) + b_4 I\left(k \in S_t \;\&\; t < 1996\right)\right] \ln\left(CompetATMs^*_{jkt}\right) \\
& + \sigma_t \ln\left(\bar{s}_{j|g}\right) + \xi_{jk} + \xi_t + \Delta\xi_{jkt}
\end{aligned} \tag{9}
$$

We address the measurement error issue by implementing the procedure in Lewbel (1997). This involves using higher moments of the observable data (both the proxies and the x_{jkt}'s) as instruments for the variables that are measured with error.[49] In the results below, we present both estimates that use this EIV-IV (Error-in-Variables Instrumental Variable) correction and estimates that do not, and discuss their differences. We also conduct some robustness checks using different imputation methods, which we present in appendix Table A1. Finally, we conduct a robustness check that compares EIV and non-EIV results in counties where we possess very complete data, and also in counties where we possess relatively incomplete data.[50] We find that that the EIV correction has the greatest effects in counties with incomplete data, suggesting that the EIV correction performs well. We present these results in appendix Table A2.

3.6.1 Endogeneity

The unobserved portion of quality that remains in the error term, $\Delta\xi_{jkt}$, is likely to be correlated with the price variable p_j and the within-nest market share $\bar{s}_{j|g}$. Increases in unobserved quality will likely be correlated with both increases in price and within group share. We account for this following following Berry (1994) and Berry, Levinsohn and Pakes (1995) by using costs and competitors' characteristics as instruments.[51]

---

[49] These instruments will provide consistent estimates of the true parameters if the joint distribution of the variables measured with error is not multivariate normal—in particular, if the distribution is skewed.

[50] One could also use the completeness of the data—for example, the fraction of banks in the local market for which we observe data—analogously to a "reliability ratio," which can be used in corrections for attenuation bias. However, such corrections maintain the assumption that the actual measurement error is correlated with this share (which we expect but can not confirm), while the Lewbel (1997) procedure makes no assumptions regarding which observations display the greatest error.

[51] Our cost measure is the bank's average loan loss rate over the previous year. The competitors' characteristics include offerings of brokerage services and money market accounts, which will vary by bank/county/year. This

3.7 Variables and Descriptive Statistics

Table II lists yearly trends for the primary variables used in our analysis. In addition to the variables discussed above, we also define a set of bank-level variables capturing other characteristics associated with deposit accounts, for inclusion in the x_{jkt} vector. We use county-level branches to measure convenience of access to non-ATM related services. We use employees per branch and salaries per employee to capture service quality. We measure the number of counties in which a bank operates, in order to allow willingness to pay to depend on the geographic breadth of a bank's operations. The average number of counties that a bank has branches in increases dramatically over the sample. This is the result of the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 that relaxed interstate branching restrictions. Finally, we define two dummy variables indicating whether the bank offers complementary services: money market accounts, and brokerage services. We would expect that increases in any of these variables would increase consumers' willingness to pay for accounts.

While we do not present the results here, in related work we examine our summary data in more detail in order to highlight the variation in our data that drives identification.[52] In that work we observe two general trends. First, much of the within-firm increases in ATM density (and competitors' ATMs) appear to be accompanied by increased prices on deposit accounts. This pattern is in fact suggested by the data in Table II as well. Furthermore, we observe that the greatest changes in behavior occur for (a) large rather than small banks, and (b) urban rather than rural banks. It appears that the post-1996 increase in ATM deployment, and any associated increase in deposit prices are concentrated primarily among large urban banks. In fact, among small urban banks ATM deployment stays essentially flat, while deposit prices actually fall. There is relatively minor variation in foreign fees or competitors' surcharges across these categories, although larger banks are more likely to impose surcharges themselves (thereby increasing competitors' surcharges for all other banks in the market). Interestingly, during all of these changes within-firm market shares are relatively stable, with the exception of small urban banks, who appear to lose some ground relative to large urban banks.[53]

implictly assumes that competitors' characteristics are exogenous from any one bank's perspective. In future work, we plan to use competitors' prices in *other* markets as an additional instrument at the bank/county/year level.

[52]See Knittel and Stango (2003) for details.

[53]Average market share falls in Table II above, but primarily due to sample composition.

4 Results

Table III reports the results from four specifications estimating equation (7).[54] The first specification uses OLS and ignores the endogeneity of prices and within-nest market share. The second specification instruments for prices and within-nest market share. The third specification implements the Error-in-Variables Instrumental Variable (EIV-IV) specification.

Patterns across the specifications seem sensible. The price coefficient grows more negative when we move to the IV specifications. The coefficients on the variables measured with error change significantly moving from the IV to EIV-IV specifications, and for the most part in an intuitive way. We expect that the competitors' ATMs and competitors' surcharges variables are measured with relatively more error than own ATMs; indeed, these coefficients change the most, and the EIV-IV estimates are farther away from zero. This suggests that the technique reduces attenuation bias.

Most of the coefficients on the x_{jkt} follow an intuitive pattern. Utility for deposit accounts increases with the number of branches, employees per branch, salary per employee and number of counties in which a bank operates. The dummy variables indicating complementary service offerings are not statistically significant, although in most specifications the coefficients are of the expected signs.

The coefficient associated with price represents the marginal utility of income, and allows us to interpret the other coefficients. It also allows us to calculate the firm-level price elasticity of demand; we show summary data regarding these elasticity estimates in Table AII. The estimates are generally quite low, lying near one for most banks. One possible explanation for this is the significant anecdotal evidence that banks use checking account prices as loss leaders, in order to engage in cross-marketing for loan and other financial service products. We plan to explore this issue further in future work.

In order to clarify the economic interpretation of our results regarding the strength of network effects, we discuss them here in terms of price changes that would leave consumers indifferent to a given change in ATMs or incompatibility. Within this context we find that the indirect network effect between a bank's own ATM density and willingness to pay is strong; in exchange for a fifty percent increase in own ATMs, the average consumer is willing to pay deposit account prices that

[54] These results are nearly identical to those from the specifications in equations 5 and 6. This is not surprising; most of the within-firm variation in $f_{jt} + E\left(s_{-j,kt}\right)$ stems from variation in $E\left(s_{-j,kt}\right)$, as firms do not change their foreign fees vey much. Similarly, most of the variation in $E\left(s_{-j,kt}\right)$ is fairly discrete and occurs in 1997 as firms initially adopt surcharging.

are roughly ten percent higher. The effect of competitors' ATMs (absent fees) is also economically significant; for a similar fifty percent increase in competitors' ATMs the mean consumer would pay deposit fees nearly twenty percent higher.[55]

We also find significant effects of incompatibility. As the costs associated with using foreign ATMs increase, the value associated with competitors' ATMs falls. At the typical foreign cost of $2.50, a proportional increase in competitors' ATMs is worth three-quarters as much as when these costs are zero. At a combined (foreign plus surcharge) cost of ten dollars, the typical customer derives no value at all from competitors' ATMs—meaning that this level of incompatibility eliminates the indirect network effect.

5 Surcharging and Consumer Welfare

The policy debate surrounding ATM fees focuses on whether consumers have been adversely affected by surcharging. Surcharging can affect consumer welfare in at least two ways. The first is the effect of incompatibility in reducing the value of competitors' ATMs. However, there is a second effect; it appears that ATM deployment accelerated after 1996, which would increase consumer welfare. Attempting to quantify the net effect of these changes requires estimating changes in deployment after 1996; given that ATM deployment was growing even before 1996, we estimate the shift in the growth rate after 1996 in order to avoid attributing all post-1996 deployment to surcharging. For each ATM related variable $\left[\ln(OwnATMs^*_{jkt}), \ln(CompetATMs^*_{jkt}), E\left(s^*_{-j,kt}\ln(CompetATMs^*_{jkt})\right), E\left(s^*_{-j,kt}\right)\right]$ we estimate:

$$y_{jkt} = \alpha_0 + \alpha_1 t + \alpha_2 I\,(yr = 97) + \alpha_3 I\,(yr = 98) + \alpha_4 I\,(yr = 99) + \varepsilon_{jkt} \qquad (10)$$

We estimate three variations of equation (10). The first is a fixed effect regression at the bank/county level. Under this specification, α_4 represents the detrended average within bank/county growth rate over the sample period. Table IV reports these results. For $OwnATMs^*_{jkt}$, the increase in the detrended increase in ATM deployment is 7 percent in 1999; for $CompetATMs^*_{jkt}$ the increase is 12 percent. The level of $E\left(s^*_{-j,kt}\ln(CompetATMs^*_{jkt})\right)$ increases by 4.6.

[55] It may seem odd that an equal percentage increase in competitors' ATMs would be worth more than in own ATMs—but the base level of competitors' ATMs is much higher, meaning that it is a significantly larger increase in the total number of ATMs. Given the parameter estimates, consumers are always willing to pay more for an additional own rather than competitors' machine.

In the second specification, we allow growth rates to vary by state by estimating equation (10) for each state in our sample, pooling the bank/county observations. While this adds noise to our detrended growth rates, it allows for state level variation in the growth rates. Finally, we estimate equation (10) at the county level. The mean of the state- and county-level estimates is similar to the aggregate measure reported in Table IV.

In Table V, we use the parameters from Table III and our estimates of the increase in ATM deployment to calculate the change in consumer welfare over the period 1994-1999. Because we have estimates of the marginal utility associated with both ATMs and incompatibility, we can use these parameters and estimates of changes in the ATM/incompatibility variables to calculate utility changes for the typical consumer. We present aggregate, state-level and within-county estimates. The aggregate estimates use the parameters from Table V, and fix the changes in ATM-related variables at their sample mean values. The within-state and within-county estimates use the individual state- or county-level parameters, which we do not show to save space. We present both dollar value and percentage figures. The dollar value numbers can be used to calculate actual dollar costs to consumers from incompatibility. Recall that the typical consumer holds \$1600 in transaction balances over the year. Thus, finding that incompatibility reduced welfare by \$0.0051 implies an annual cost of \$8.16—or, roughly the cost of five foreign ATM transactions per year.

We provide both the partial effects of incompatibility holding ATM deployment constant, and fuller estimates incorporating the welfare gains from increased deployment. On balance, the partial effects amount to a reduction in consumer welfare equivalent to an increase in deposit fees of roughly nine percent (or nine dollars per customer per year). Greater ATM deployment during our sample period increases consumer welfare. However, an unweighted average across our observation still shows the net effect on consumer welfare is a reduction equivalent to a 4-6% increase in deposit fees.

To provide some evidence on cross-market differences, Figure 1 shows a kernel density estimate of the percentage change in welfare from 1994 to 1999 for all counties in our sample. The figure shows both the partial and full estimates. The full estimates vary widely because we estimate significant variations across counties in the post-1996 shift in ATM deployment, and are positive for a substantial share of counties. Some of this heterogeneity may simply reflect noise in our estimates of county level changes. Nonetheless, it seems clear that there are some counties in which ATM deployment expanded extremely rapidly, and perhaps rapidly enough that the gains from increased deployment may have offset the effects of incompatibility. It further appears that many of these areas are urban markets. Figure 2 plots our estimated county-level welfare changes against the natural logarithm of county population density. The figure also includes a non-parametric

Lowess smoothed line. There appears to be a significant positive relationship between the two and the non-parametric line is positive for population density levels above 400. A simple linear regression confirms this, yielding the following estimated relationship:

$$\begin{aligned} UtilChgPercent_k &= \underset{(0.028)}{-0.329} + \underset{(0.005)}{0.056}\ln(PopDens_k) \end{aligned} \tag{11}$$

While this estimate is admittedly rough, it predicts negative welfare effects for any county with population density below 356 persons per square mile—a figure typical of such medium-sized metropolitan areas as Kalamazoo county (Michigan) and Palm Beach county (Florida). Of the roughly nine hundred counties in our sample, over six hundred fall below this level. Another way of interpreting the results is that in a sparsely populated area such as Des Moines county (Iowa) with a population density of roughly 100 people per square mile, the model implies a welfare change of negative seven percent—while in a densely populated area such as Montgomery county (Maryland) with 1500 people per square mile, the model implies a welfare change of positive seven percent.

The above results regarding population density depend solely on differences in ATM deployment across markets, but it is also possible that demand parameters vary across markets. In particular, it seems likely that areas with high population density have higher travel costs. This might increase consumers' willingness to pay for ATM services, since using ATMs involves traveling to them. To analyze the effects of travel costs further, we estimate equation (7) separately for counties above and below the median population density level. Lower travel costs should reduce the importance of ATM density as well as reduce the surcharge level for which competitor's ATMs are no longer valued. The results for the ATM variables are reported in Table 6. In low population density markets, the value placed on ATMs is much lower and not statistically significant, while the "break even" foreign costs falls to under three dollars. In contrast, high density markets place a greater weight on ATMs and competitors' ATMs are valued even with very high foreign costs.[56]

Table 7 repeats the welfare counterfactual using these parameters, while Figure 3 plots these welfare changes versus the log of population density for the base and split-sample models; the results are striking. Consumers in high travel cost counties benefit from the imposition of surcharges as travel costs were reduced from the greater ATM presence; the net effect remains negative for consumers in low travel cost counties. Figure 4 plots a Lowess smoothed line through the welfare

[56]These are results are consistent Knittel and Stango (2004) which suggests the bulk of the reduced form relationship between prices and ATM density comes from the high density markets.

scatterplot (note the change in scale). Comparing this to Figure 2 suggests that the welfare effect of surcharging becomes positive at a lower population density and has a steeper slope than implied by the base model.[57] While we repeat the caveat that these calculations ignore any shifts in the intensity of price competition following surcharging, these results do suggest that surcharging may have a positive effect on consumer welfare, especially if we focus on a population weighted average of consumer welfare.

6 Alternative Specifications

Tables A1-A3 report the results of the robustness checks we mention earlier in the paper. Table A1 shows that in counties where we observe relatively complete ATM data, the EIV results are fairly similar to non-EIV results. In counties with incomplete data this is not true, suggesting that our EIV-IV approach is correcting at least some of the bias.

We next estimate the model using three different imputation methods for the competitors' ATMs. These results are described and reported in Table A2. For the most part, the results are robust to these alternative imputation methods. While the coefficient associated with competitors' ATMs increases substantially in the last three models, this is because these models predict lower levels of competitors' ATMs. The welfare changes resulting from post-1996 changes in ATM deployment and incompatibility are nearly identical in each case.

We also test the robustness of our results to the incompatibility measure. While the standard errors are larger when using these alternative measures, the general pattern of the coefficients is unchanged.

7 Conclusions

In this paper, we estimate the importance of network effects and incompatibility in a classic "hardware/software" industry: Automated Teller Machines (ATMs) and ATM cards. Our empirical setting represents a rare opportunity to measure the level of incompatibility and a relatively discrete change compatibility between cards and ATMs. We estimate a structural model of consumer demand for deposit accounts (ATM cards), allowing demand to depend not only on prices and characteristics directly associated with the account, but also on the ATM services provided indirectly with the account.

[57] The linear relationship is: $UtilChgPercent_k = -0.435 + 0.081 \ln(PopDens_k)$.

We find that ATM-related services play an important role in consumer behavior regarding deposit accounts. A bank's own ATMs significantly affect the demand for its deposit account services. We also find a strong indirect network effect; consumers' willingness to pay for deposit accounts is affected as well by the availability of competitors' ATMs in the local market. This suggests that other research examining ATM fees should consider the interplay between ATM fees, ATM deployment and the demand for complementary deposit account services. More generally, our results suggest that conducting partial analysis of markets where these effects matter may yield misleading inference regarding consumer and/or firm behavior.

Most importantly, we identify a clear relationship between consumer behavior and the compatibility of products within the network system comprised by ATMs and cards. Surcharging significantly reduces the indirect network effect associated with competitor ATMs. In the current version of the paper, we employ the estimated parameters from this model to investigate a number of questions. We calculate the change in consumer welfare from the introduction of surcharging, accounting for both the change in compatibility and the increase in the number of ATMs. We find that consumer welfare falls in markets where deployment does not offset the effects of incompatibility. We do find, however, that the largest markets—which also have higher population density—experience increased welfare. It is possible that this result would be even stronger if we considered the impact of (unobserved) ATM deployment by ISOs, who typically concentrate their ATMs in metropolitan areas.[58] This result has important implications for the policy debate in ATM markets, and also furthers our understanding of the relationship between incompatibility and consumer welfare more generally. In particular, it suggests that while incompatibility *ceteris paribus* harms consumers, it can also provide strong incentives for investment in product quality. To use an analogy from another hardware/software market, it suggests that the simultaneous existence of incompatible video game consoles (XBox and Playstation) may benefit rather than harm consumers. Consumers can not mix and match games with consoles because some games are proprietary to each console system. However, this arrangement may increase hardware developers' incentives to vertically integrate and invest in developing high-quality games. Indeed, both Sony and Microsoft devote tremendous sums to in-house development of their propritary "flagship" games.

In future work we plan to complement our demand-side analysis of ATM markets with a supply-side model of firm behavior. At the simplest level, it should allow us to estimate the degree to which incompatibility affects the intensity of price competition. Given that this is an open

[58]Dove Consulting (1999) estimates that ISOs had deployed 20,000 ATMs by 1999—roughly ten percent of the total deployed by banks. If all of this deployment could be attributed to incompatibility, and much was concentrated in areas of high population density, our estimates of welfare gains in urban areas might be significantly higher.

theoretical question, we feel it is a useful empirical endeavor. Such an exercise should also allow us to estimate the social welfare implications of policies that force compatibility, taking into account both consumer and producer surplus. In particular, we will be able examine whether the market displays "too much" incompatibility, or whether incompatibility leads to socially excessive deployment of ATMs.

From a competition policy standpoint, we also may be able to identify the degree to which banks use surcharges as a competitive device. Given the allegations that large banks use surcharges to intentionally create incompatibility and siphon customers away from smaller banks, this is an important line of inquiry. More generally, such analysis will improve our understanding of firms' strategic use of incompatibility in network markets—an idea at issue in many recent antitrust cases.

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A Appendix

A.1 Tables

Table I: ATM Deployment, Fees and Usage 1994-1999

Sources: Fee data from the Federal Reserve Board's Annual Report to the Congress on Retail Fees and Services of Depository Institutions, various years. Other data from Faulkner and Gray's Card Industry Directory, various years. Figures for total ATM deployment include ATMs deployed by banks and ISOs.

Variable:	1994	1995	1996	1997	1998	1999
ATM Fees:						
Percent banks charging foreign fee:	78.4	85.3	79.8	67.0	74.5	72.3
Average foreign fee:	0.95	1.03	1.10	1.06	1.10	1.17
Percent banks charging surcharge:	—	—	44.8	60.1	77.9	82.9
Average surcharge:	—	—	1.19	1.14	1.20	1.26
ATMs (1000s):	109	123	139	165	187	227
ATM Cards (millions):	185	190	194	200	206	217
Annual ATM Transactions:	705	807	890	915	930	907
per card	45.7	51.0	55.1	54.9	54.2	50.2
per ATM (1000s)	77.5	79.0	76.8	66.5	60.0	48.0

Table II: Yearly Means

Variable:	1994	1995	1996	1997	1998	1999
Deposit Share	0.147	0.142	0.139	0.137	0.136	0.121
ATMs	11.1	11.1	11.1	13.9	16.3	16.7
Competitors' ATMs	128.1	108.8	106.2	122.5	150.7	179.5
Account Fees ($ per dollar of deposits/year):						
Excluding Opp. Cost of Funds	0.006	0.005	0.008	0.010	0.011	0.013
Including Opp. Cost of Funds	0.048	0.062	0.058	0.060	0.060	0.057
Foreign Fee ($)	1.34	1.42	1.52	1.48	1.56	1.54
Competitors' Surcharges ($)	0	0	0	0.81	1.01	1.25
Branches	8.7	8.5	8.9	8.7	8.7	8.5
Employees/Branch	23.4	22.1	21.4	21.4	22.9	21.4
Salary/Employee ($1000)	17.1	18.1	20.0	20.2	21.1	22.6
Number of Counties	16	17	23	43	66	79
Share with MM Accounts	0.997	0.996	0.997	0.999	0.999	1.000
Share with Brokerage Svcs.	0.729	0.737	0.767	0.842	0.881	0.894

Observations are at the bank/county/year level. Number of observations is 9348.

Table III: Nested Logit Results – Using variation in $f + E(s_{-j,kt})$

Variable:	OLS	IV	EIV-IV
$Price$	-1.42	-13.00^{***}	-11.63^{***}
	(1.08)	(4.84)	(4.83)
$\ln(ATMs)_j$	0.044^{***}	0.140^{***}	0.098^{***}
	(0.013)	(0.020)	(0.026)
$\ln(ATMs)_{-j}$	0.110^{***}	0.092^{***}	0.174^{***}
	(0.014)	(0.026)	(0.033)
$\ln(ATMs)_{-j} \times (f + E(s_{-j,kt}))$	-0.011^{***}	-0.010^{**}	-0.014^{***}
	(0.004)	(0.005)	(0.005)
$\ln(ATMs)_{-j} \times I(k \in S_t \ \& \ t < 1996)$	-0.008	-0.009	-0.016
	(0.020)	(0.030)	(0.022)
$Branches$	0.010^{***}	0.022^{***}	0.014^{***}
	(0.002)	(0.003)	(0.003)
$Employees/Branch$	0.0004	0.0011^{**}	0.0005^{*}
	(0.0003)	(0.0006)	(0.000)
$Salary/Employee$(\$1000)	0.002	0.004^{*}	0.003^{*}
	(0.002)	(0.002)	(0.002)
$\ln(Number\ of\ counties)$	0.017^{***}	0.074^{***}	0.045^{**}
	(0.016)	(0.020)	(0.018)
$Offer\ MM\ Accounts$?	0.121	0.094	0.119
	(0.179)	(0.197)	(0.183)
$Offer\ Brokerage\ Svcs.$?	0.000	-0.013	-0.004
	(0.021)	(0.023)	(0.022)
σ	0.832^{***}	0.412^{***}	0.662^{***}
	(0.015)	(0.067)	(0.053)
$\sigma \times I(year = 1995)$	-0.004	-0.030	-0.018
	(0.009)	(0.019)	(0.017)
$\sigma \times I(year = 1996)$	-0.025^{***}	-0.065^{***}	-0.056^{***}
	(0.009)	(0.020)	(0.018)
$\sigma \times I(year = 1997)$	-0.018^{*}	-0.057^{***}	-0.049^{**}
	(0.010)	(0.021)	(0.020)
$\sigma \times I(year = 1998)$	-0.035^{***}	-0.078^{***}	-0.060^{***}
	(0.011)	(0.024)	(0.022)
$\sigma \times I(year = 1999)$	-0.060^{***}	-0.118^{***}	-0.090^{***}
	(0.013)	(0.028)	(0.025)
Instruments:			
Price and within share?	No	Yes	Yes
Measurement Error?	No	No	Yes
*** — significant at .01 or better			
** — significant at .05 or better			
* — significant at .10 or better			

Notes: N=9348. Standard Errors are in parentheses. All specifications include bank/county and year fixed effects.

Table IV: Aggregate Post-1996 Shifts in ATM-Related Variables

	Dependent Variable:			
Variable:	$\ln(ATMs)_j$	$\ln(ATMs)_{-j}$	$(f_{jt} + E(s_{-j,kt}))$	$\ln(ATMs)_{-j} \times (f_{jt} + E(s_{-j,kt}))$
t	0.101***	0.081***	0.086***	0.393***
	(0.006)	(0.005)	(0.004)	(0.023)
$I(year = 1997)$	0.072***	0.077***	0.704***	2.854***
	(0.016)	(0.011)	(0.011)	(0.058)
$I(year = 1998)$	0.045**	0.098***	0.908***	3.776***
	(0.022)	(0.016)	(0.015)	(0.080)
$I(year = 1999)$	0.032***	0.116***	1.024***	4.525***
	(0.014)	(0.020)	(0.019)	(0.103)

Standard errors in parentheses. Bank/County fixed effects also included.

Table V: Estimated Welfare Changes, 1994-1999

This table reports means and standard deviations of estimated welfare changes from surcharges. The first three calculations hold ATMs constant, while the final three account for the increased growth of ATMs. We use three methods for estimating the growth rates in the ATM-related variables. "Within-County Changes" estimates a single regression with county fixed effects. "State-Level Changes" estimates a separate regression for each state in our sample. Finally, "County-Level Changes" estimates a separate regression for each county in our sample. Calculations use sample average 1994-1999 shifts in ATM-related variables (see Table IV). Price units are dollars per year, per dollar of transaction deposit balances. Percent figures divide price unit changes by (bank-level) prices.

	Metric:	
	Price Units ($)	Percent
Surcharging Only:		
Within-County Changes	−0.0051	−9.01%
	(0.0017)	(3.44)
State-Level Changes	−0.0053	−9.54%
	(0.0037)	(6.86)
County-Level Changes:	−0.0049	−8.74%
	(0.0042)	(7.85)
Surcharging and ATM Deployment:		
Within-County Changes	−0.0034	−6.05%
	(0.0017)	(3.26)
State-Level Changes	−0.0020	−3.77%
	(0.0272)	(48.50)
County-Level Changes	−0.0026	−4.59%
	(0.0131)	(23.82)

Table A1: Nested Logit Results—Observability and EIV-IV Results

	Card ID Share>50%		Card ID Share<50%		
Variable	No EIV	EIV	No EIV	EIV	diff-in-diff
$\ln(ATMs)_j$	0.172	0.071**	−0.074	0.111***	−0.084
	(0.164)	(0.036)	(0.183)	(0.034)	
$\ln(ATMs)_{-j}$	0.096	0.131***	0.298**	0.144***	−0.119
	(0.101)	(0.051)	(0.118)	(0.042)	
$\ln(ATMs)_{-j} \times (f_{jt} + E(s_{-j,kt}))$	−0.025	−0.010	−0.111***	−0.021***	−0.075
	(0.025)	(0.007)	(0.038)	(0.008)	
Observations	3778		5360		

Standard Errors are in parentheses. Bank/County and year fixed effects are also included.

*** denotes significance at the .01 level, ** significance at the .05 level, and

* denotes significance at the .10 level.

Table A2: Alternative Imputation Methods

Model 2 measures issuer size using categorical variables rather than the logarithm of deposits. Model 3 imputes one ATM per branch for those which lack data. Model 4 sets ATMs per branch for these banks equal to the median for observed banks within the same deposit level quartile. Model 5 sets ATMs per branch equal to the median for observed banks within the same deposit level quartile for MSAs and non-MSAs.

Variable	Base	Model 2	Model 3	Model 4	Model 5
$\ln(ATMs)_j$	0.098***	0.105***	0.091***	0.059	0.043
	(0.026)	(0.026)	(0.026)	(0.059)	(0.056)
$\ln(ATMs)_{-j}$	0.174***	0.115***	0.179***	0.416***	0.420***
	(0.033)	(0.025)	(0.032)	(0.042)	(0.042)
$\ln(ATMs)_{-j} \times (f_{jt} + E(s_{-j,kt}))$	−0.014****	−0.014***	−0.016***	−0.021***	−0.021***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)

Standard Errors are in parentheses.

*** denotes significance at the .01 level, ** significance at the .05 level, and

* denotes significance at the .10 level.

Table A3: Alternative Measures of Incompatibility

Model 2 uses expected surcharges for the incompatibility measure, while Model 3 uses a post-1996 indicator variable.

Variable	Base	Model 2	Model 3
$\ln(ATMs)_j$	0.098***	0.126***	0.131***
	(0.026)	(0.028)	(0.026)
$\ln(ATMs)_{-j}$	0.174***	0.115***	0.145***
	(0.033)	(0.036)	(0.034)
$\ln(ATMs)_{-j} \times Incomp$	−0.014****	−0.044	−0.033
	(0.005)	(0.035)	(0.029)

Standard Errors are in parentheses.
*** denotes significance at the .01 level,
** significance at the .05 level, and
* denotes significance at the .10 level.

Table A4: Estimated Price Elasticities

	Mean	Median	25th Percentile	75th Percentile
Own Price Elasticity	1.214	1.195	1.023	1.372

Table A5: High and Low Travel Cost Markets

Low travel cost markets are defined as having a population density below the median, while high travel cost markets are defined as having a population density above the median.

Variable	Low Travel Costs	High Travel Costs
$\ln(ATMs)_j$	0.025	0.134***
	(0.048)	(0.026)
$\ln(ATMs)_{-j}$	0.077	0.269***
	(0.060)	(0.034)
$\ln(ATMs)_{-j} \times (f_{jt} + E(s_{-j,kt}))$	−0.026**	−0.010**
	(0.012)	(0.005)

Standard Errors are in parentheses.

Bank/County and year fixed effects are also included.

*** denotes significance at the .01 level,

** significance at the .05 level, and

* denotes significance at the .10 level.

A.2 Figures

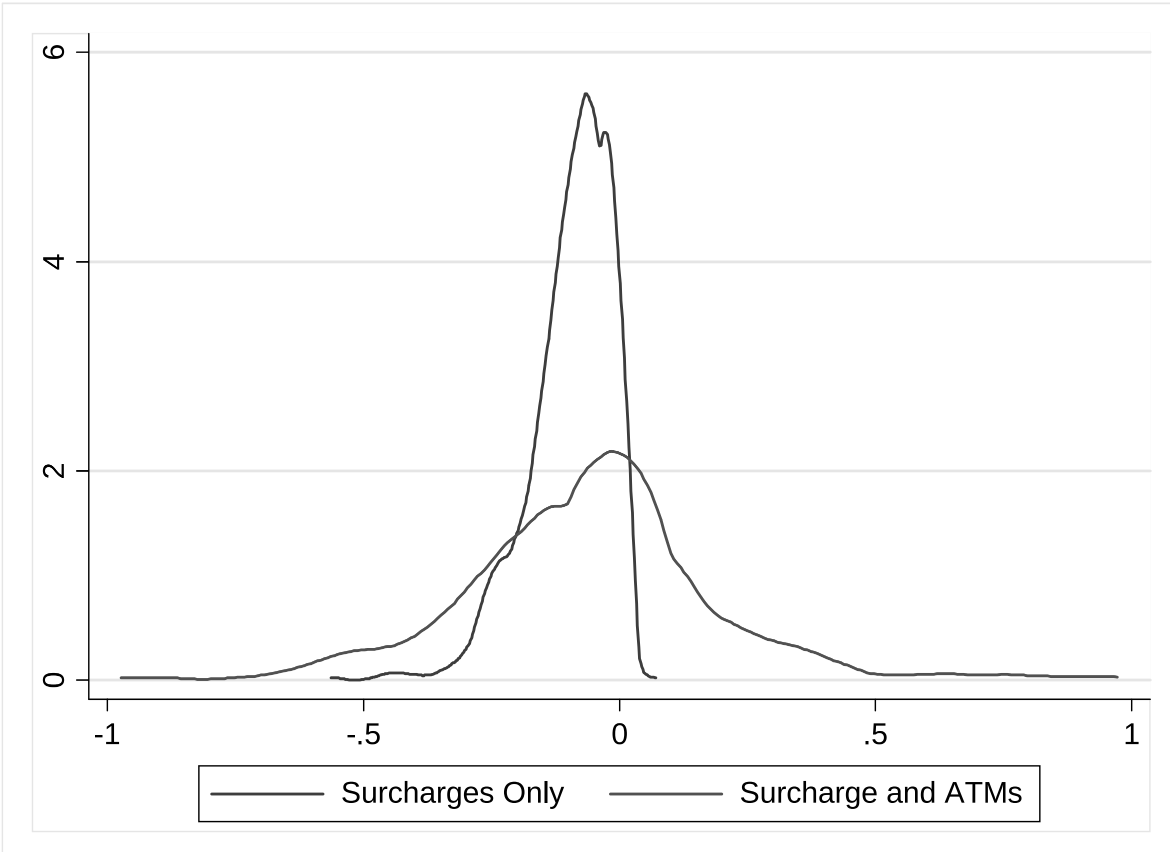

Figure 1: Kernel Density Estimate of County-Level Welfare Changes

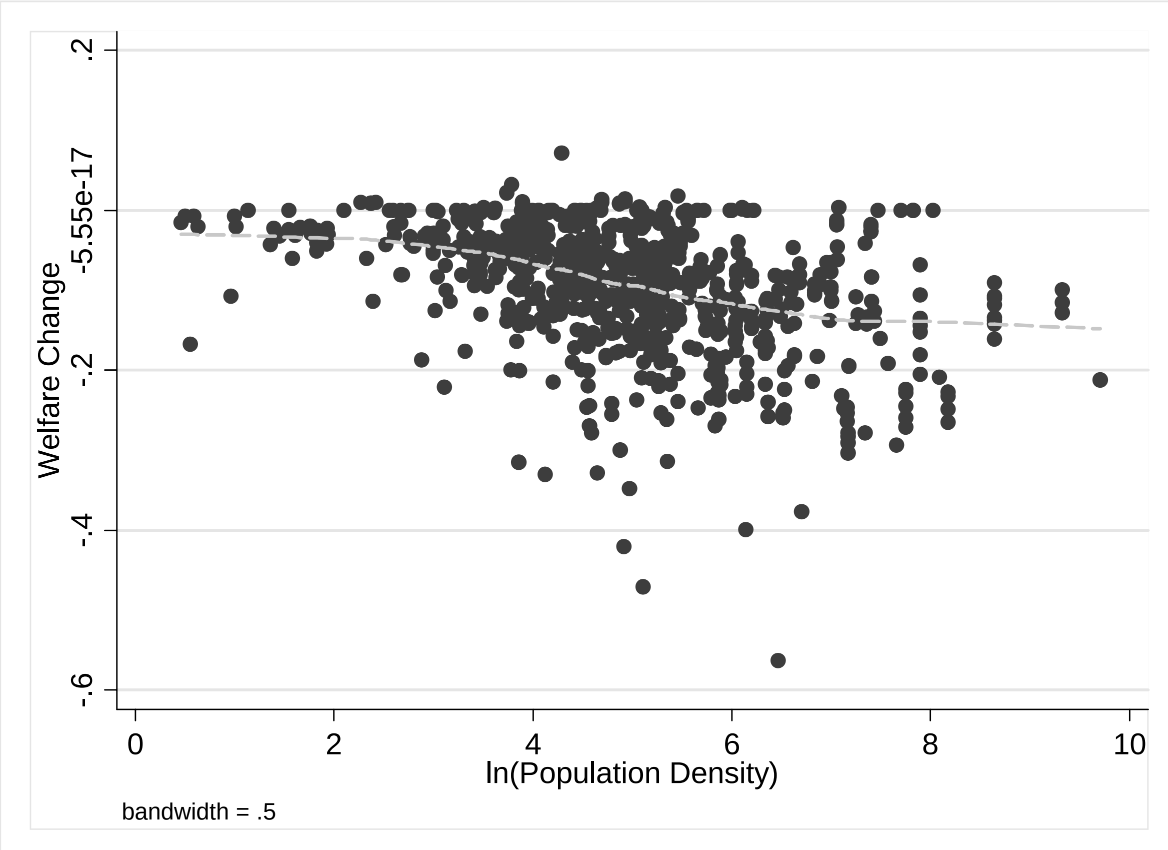

Figure 2: County-Level Welfare Changes and Population Density – Surcharging Only

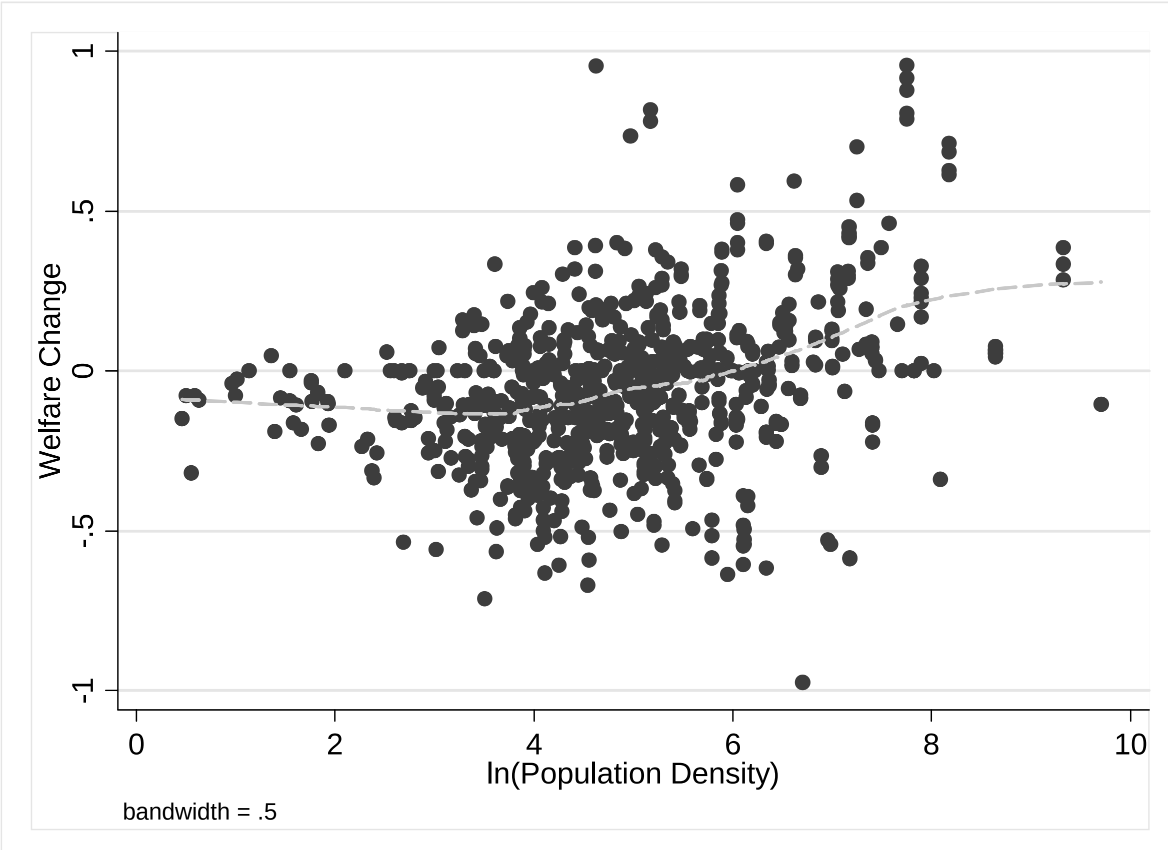

Figure 2: County-Level Welfare Changes and Population Density

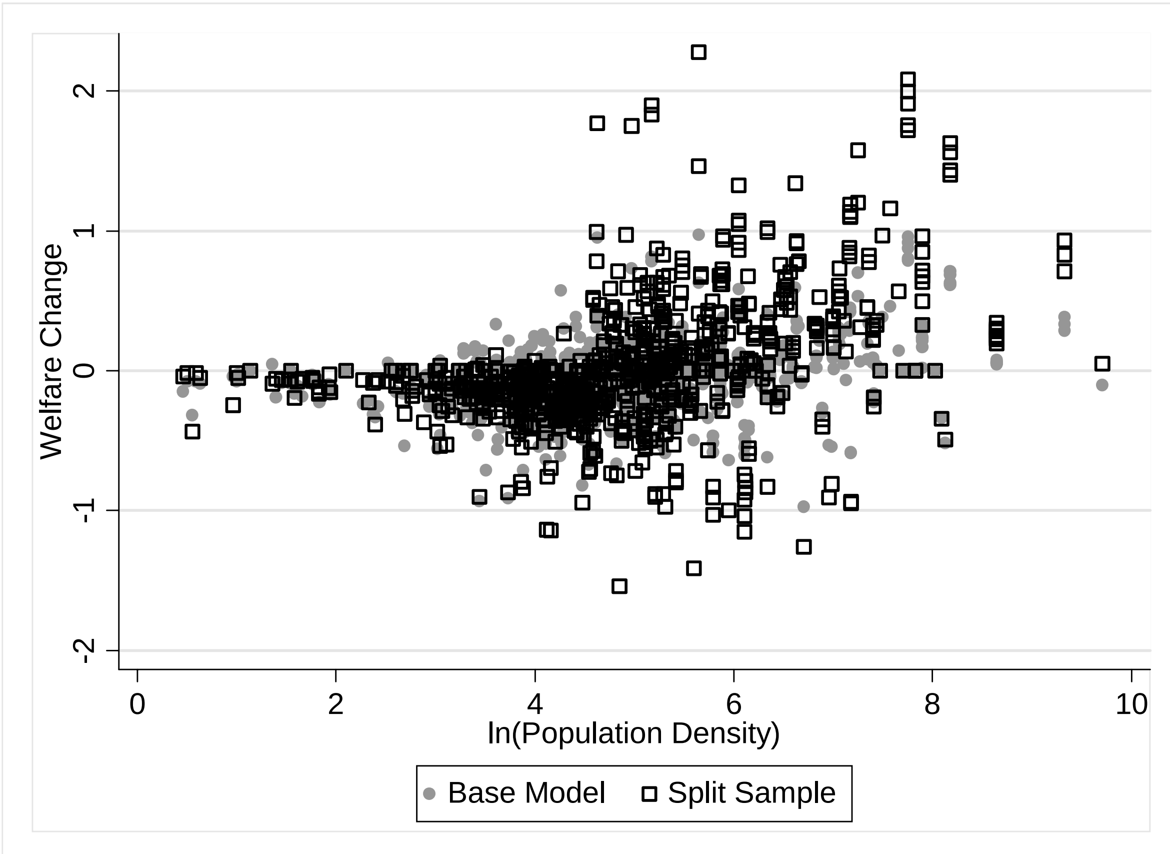

Figure 3: County-Level Welfare Changes For Base Model and Split Sample Model

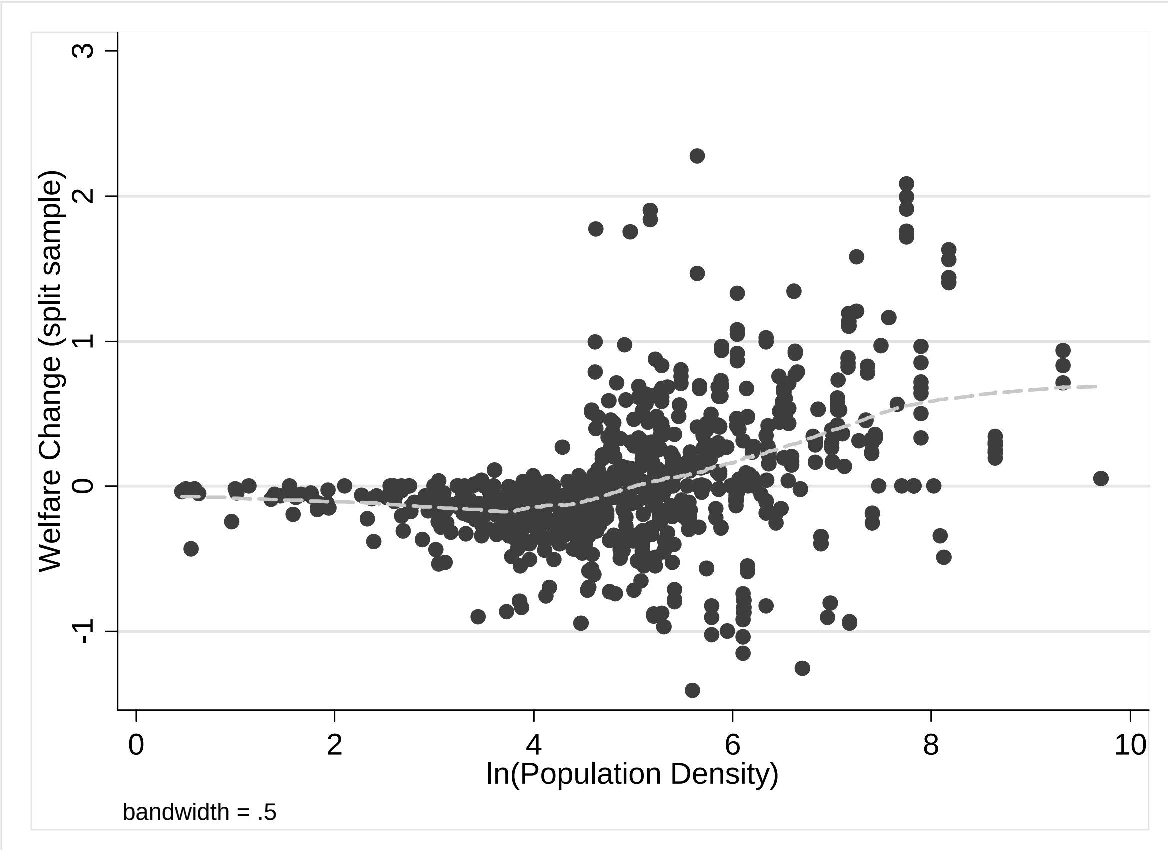

Figure 4: Split Sample Welfare Changes and Population Density