Quantifying Equilibrium Network Externalities in the ACH Banking Industry[1]

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Abstract

We seek to estimate the causes and magnitudes of network externalities for the automated clearinghouse (ACH) electronic payments system, using a panel data set on individual bank adoption and usage of ACH. We construct a model of ACH usage where we can identify network externalities from correlations of increases in usage levels for banks within a network, and from increases in usage following exogenous increases in market concentration or size of competitors. Using geographic data, we construct a data set of localized networks. We structurally estimate the parameters of the model by matching equilibrium behavior to the data, using a method of simulated moments estimator. This estimation provides evidence on the magnitudes of the network effects and on the frequency that the ACH market is stuck in a Pareto inferior equilibrium.

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1. Introduction

The goal of this paper is to estimate the size and importance of network externalities for the automated clearinghouse (ACH) banking industry using an equilibrium model of ACH usage. ACH is an electronic payment mechanism developed by the Federal Reserve and used by banks. ACH is a network: banks on both sides of a transaction must adopt ACH technology for an ACH transaction to occur. Network externalities are thought to exist in several high-technology industries. Examples include fax machines, where network effects may exist because two separate parties must communicate for a transaction to occur and computers, where network effects may exist because information on how to use new technology is costly. ACH shares the network features of fax machines, computers and other technological goods, and hence network externalities may exist for ACH.

If present, network externalities typically cause underutilization of the network good. Moreover, there is the possibility of multiple equilibria. When the network externality is positive, Nash equilibria with network externalities can be Pareto ranked, and it is possible that additional underutilization may result from the industry being stuck in a Pareto inferior equilibrium. This is particularly relevant for the case of ACH. In an age when computers and technology have become prevalent, most payments continue to be performed with checks and cash. By estimating the magnitude of network externalities, we can further understand the causes of such externalities, uncover how much the usage of ACH differs from the socially optimal level, and find out whether markets are stuck in Pareto inferior equilibria. Moreover, as we are estimating an equilibrium model, we can evaluate the welfare and usage consequences of policies such as government subsidies of the network good.

In previous work, two of us (Gowrisankaran and Stavins (1999) – hereafter GS) used bank-level panel data on ACH usage in order to test for the presence of network effects and externalities. In that work, we developed a theoretical framework which gave conditions under which network externalities are identified using panel data. Under these conditions, network effects are indicated if usage by banks within a local area are correlated conditional on bank and

time fixed-effects. That paper extended the recent literature on network externalities that used cross-sectional data (see Goolsbee and Klenow (1998) and Rysman (2000)) by using panel data. The panel data allow for the separation of network externalities versus regional correlation in preferences, although a necessary identification assumption is that these correlations are time invariant. The study ran a reduced form regression of usage on the usage by other banks in the network allowing for fixed effects and found significant evidence that network effects exist. The paper also developed an indirect test for the externalities resulting from network externalities. The intuition for this test is that externalities are partially internalized if there are less firms. This second test regressed ACH usage against market concentration. Externalities were indicated since higher market concentration was correlated with more ACH usage.

While these regressions can be used to *test* for network externalities, they are not sufficient to *estimate the magnitude* of network externalities. In the regression of usage on usage, note that the observed correlation between banks adoption decisions implies that there is a network effect, the magnitude of the correlation is not the same as the magnitude of the structural network effect. This is because the correlation reflects a Nash equilibrium in usage decisions. Alternately put, with network effects, the usage levels of other banks will be endogenous, and thus the estimated correlations are not the structural responses. Additionally, the regression of usage on concentration is a standard reduced-form regression that does not uncover the structural parameter. An estimation process that explicitly solves for the Nash equilibrium usage levels is needed to quantify the network effects.

The current study furthers on the previous work by doing exactly this: we structurally estimate the level of network externalities with an equilibrium model. The essence of our structural estimation process is as follows: we specify a game theoretic equilibrium model of adoption and usage for ACH. Conditional on a parameter vector, we solve for the Nash equilibrium of the model for each market and then evaluate how closely the equilibrium predictions of the model match the observed data. We then search for the parameter vector that most closely matches the equilibrium predictions of the structural model to the data. Our estimation here is structural in the sense that it recovers the structural network effect parameters

by solving for the equilibrium of a full behavioral model. This study identifies the structural network parameters via a model that captures the insights of both of the reduced form tests in GS.

Our model is as follows. We consider a localized market with a given number of banks and consumers. Banks exogenously differ in size, i.e. the amount of assets under their control. In each time period a two-stage game is played. In the first stage, banks make the decision of whether to adopt ACH capabilities or not. This decision is based on weighing a fixed cost of adoption versus the marginal profits earned from ACH transactions conditional on adoption. In the second stage consumers at banks that have adopted ACH choose how many ACH transactions to make. The probability that a particular transaction is made through ACH is allowed to depend on network variables such as the number of other banks in the market that has adopted. We allow for bank and market-specific random effects to separate out the effect of regional correlations in preferences and allow for a time trend and price variables to separate out the effect of increased usage over time. As is often the case with network externalities, there are multiple equilibria in our model. We assume that the world is characterized by some frequency of best and worst equilibria. We estimate our model with quarterly panel data on small local markets with 10 or less banks.

Two broad questions generally arise regarding structural estimation. First and most importantly, what aspects of our data identify the structural parameters of our model? Second, what methodology do we use to match the equilibrium predictions of the structural model to the data? We address both of these questions below.

In terms of identification, our data will identify the network effects via two separate sources, which we use jointly and independently. The first source is covariance restrictions, which is the same basis as the test for network effects from GS. We assume that after controlling for bank characteristics including random effects that are constant across time, unobservables affecting adoption are independently distributed across banks in a given market. This allows us to identify network effects from correlations in usage. Note that this source of identification is removed if one allows for market specific random effects that vary over time.

The second source of identification is exclusion restrictions, based on the tests for externalities in GS. Suppose that there are two banks, A and B, in a network. Then, the idea here is that exogenous increases in B's assets will not enter into A's profits from using ACH, but will affect B's adoption probability and through that affect A's adoption probability. As the exogenous variables of other banks are excluded variables, they are essentially instruments, and identification follows from the same logic as in instrumental variables. Note that this source of identification will still be present even with market-specific random effects.

Importantly, we perform robustness tests where we estimate the model using only one of the two sources of identification. For example, to remove the first source of identification, we allow for market specific unobservables that vary over time. This procedure gives us a good idea of exactly which assumptions are telling us what about the parameters of our model and network externalities. Compared to the tests in GS, the structural estimates derived here are certainly much less robust to misspecification. However, we are able to combine the different sources of identification (correlation and excluded variables) and the different dependent variables (ACH adoption and usage levels) into one consistent framework.

In terms of the econometric method, we use the method of simulated moments with indirect inference. We need a simulation estimator because our model is straightforward to solve for a given vector of parameters and draws on econometric unobservables, but is impossible to solve analytically. The method with the best asymptotic properties is maximum likelihood. However, our endogenous variable is a mixed discrete-continuous variable since we observe banks either adopting or not adopting ACH, and conditional on adoption, we observe the number of transactions. Because of this, it would be very hard to apply simulated likelihood techniques. Instead, we use indirect inference, which essentially uses reduced-form regression parameters as moments. The first step is to run a set of regressions on the actual data. Then, given structural parameters, one simulates data and runs these same regressions on the simulated data. Estimates of the structural parameters are chosen to most closely match the regression estimates of the simulated data to those of the true data. The central advantage to using indirect inference over standard simulated moments is that it is easier to understand exactly what in the data identifies

parameters. Standard simulated moments would also result in an unwieldy number of moment conditions.

Preliminary results show that network externalities appear to be significantly positive and quite large in magnitude. Moreover, it does not appear that we are stuck in a bad equilibria. To the contrary, the model predicts that almost every market is in the Pareto best equilibrium.

The remainder of this paper is divided as follows. Section 2 describes the model. Section 3 describes the data. In Section 4, we detail our estimation procedure, including the computation of the equilibrium and identification of the parameters. Section 5 contains results and Section 6 concludes.

2. The Model

We propose a simple static model of network externalities at the market level. Consider a localized group of J banks at time t, each with a given number of customers. The timing of our game is as follows. In the first stage, banks simultaneously decide whether or not to adopt ACH technology. Let $A_t=(A_{1t},\ldots..,A_{Jt})$ be a set of indicator functions representing these adoption decisions. In the second stage, consumers decide whether to make their transactions using ACH or using checks. For a consumer to make an ACH transaction, their bank must have adopted ACH technology ($A_{jt}=1$). Assume that all econometric unobservables are common knowledge to all firms, and are unobservable only to the econometrician. We proceed by first analyzing consumer decisions conditional on A_t. Then we move to the first stage and analyze equilibrium bank decisions.

Since ACH transactions are a small percentage of a bank's total business, we assume that the bank's consumer base and assets are exogenous to our model of ACH usage. Denote the assets under bank j's control as x_{jt}. Assume that the number of total (both ACH and check) transactions that bank j's consumers engage in at time t is a function of assets x_{jt} and an econometric unobservable $\varepsilon_{j,t} \sim N\left(0, \sigma_{\varepsilon}^2\right)$, i.e.,

(1) $$T_{jt} = f(x_{jt}, \varepsilon_{jt}) = \lambda\left(x_{jt} + \varepsilon_{jt}\right).$$

We assume that the demand for transactions is perfectly inelastic, and hence the prices of transactions do not enter into (1). We feel that this is a reasonable assumption because the demand for transactions is likely to be very inelastic and again because ACH is a small proportion of transactions.

While transactions prices do not affect the overall number of transactions, we do allow transaction prices to affect the ratio of ACH to check transactions. Conditional on bank j adopting ACH at time t, let the probability that a given transaction is made through ACH be given by:

(2) $$P_{jt} = \frac{\exp[U_{jt}]}{1+\exp[U_{jt}]}$$

where

(3) $$U_{jt} = \beta_0 + \beta_1 u1_t + \beta_2 u2_t + \beta_3 p_{jt}^{ACH} + \beta_4 p_{jt}^{CHK} + \beta_5 t$$

Thus, the probability in (2) depends on the prices of ACH and check transactions, and two network effects variables, $u1_t$, and $u2_t$. These network effects variables measure the extent to which banks in the market have adopted ACH. Precisely, define:

(4) $$u1_t = \frac{\sum_j A_{jt} T_{jt}}{\sum_j T_{jt}}, \; u2_t = \frac{\sum_j T_{jt}^{ACH}}{\sum_j T_{jt}},$$

where. T_{jt}^{ACH} is the number of ACH transactions at bank j. In (4), $u1_t$ is simply the asset-weighted proportion of banks that adopt at t, and $u2_t$ is the proportion of transactions that are made using ACH. We assume throughout the paper that $\beta_1, \beta_2 \geq 0$, so that there is no negative network externality.

We choose to model network externalities with this bivariate functional form because there are a couple of separate reasons why usage levels might affect the probability of a given transaction being made through ACH. First, there is a direct usage externality: both the sending bank and the receiving banks must have adopted ACH for an ACH transaction to occur. Second, there may be informational externalities among consumers. If consumers are uncertain about how to use ACH or what the value of ACH is, the fact that a higher proportion of nearby consumers are using ACH may mitigate these informational problems and increase the likelihood that a given transaction is made through ACH.

Combining (1) and (2) gives the number of ACH transactions at bank j,

$$(5) \qquad T_{jt}^{ACH} = P_{jt} T_{jt} A_{jt}\,.$$

Two important assumptions are embodied in (5). First, we are assuming that there are sufficiently many transactions per bank that P_{jt} is not just the probability that a transaction is made with ACH but also the exact share of transactions that are made with ACH. Second, by multiplying the probability in (5) by A_{jt}, we are assuming that a transaction can only be made with ACH if the bank has adopted ACH.

Note that the above interpretation of our model of transaction choice does not explicitly consider underlying primitives, such as the utility functions of consumers. This interpretation corresponds to a scenario where consumers care only that a transaction is made - they do not care whether it is completed by check or by ACH. An alternative interpretation of the model would be to consider (3) with the addition of a logit error term as a discrete choice utility function. In this interpretation, consumers' receive different utility levels from check and ACH transactions, choosing the one that gives the highest utility. Importantly, there is no difference between the two interpretations in computing equilibria or in estimating the parameters of the model.

However, there is a difference if we want to do any welfare calculations using the model. For example, suppose that prices of ACH and check transactions are exactly the same. In the first interpretation, the only benefit from increased ACH usage is its lower marginal cost (for consumers, a transaction is a transaction, regardless of its type). On the other hand, in the second interpretation there *is* some utility benefit from the ability to use ACH transactions. When we examine policy experiments such as subsidizing the network good, we typically use the first interpretation. As this ignores any potential gains to consumer utility, it should give a conservative estimate of the benefits of such a policy.

Note also that we allow for a time trend in the transaction choice (3). The time trend is strictly not a structural parameter, in the sense that consumers do not care about the date when making a transaction decision. More likely, the time trend will pick up changes in the network benefit over time due to higher levels of usage from banks outside the local area. By ignoring the time trend in our policy analysis, we are again providing a lower bound on the increase in usage that can come from internalizing the network externality.

We next turn to optimal bank adoption decisions conditional on the above model of transaction choice. Recall that in the first stage, banks simultaneously decide whether to adopt ACH technology. Denote the marginal cost to the bank of an ACH and a check transaction as mc_{jt}^{ACH} and mc_{jt}^{CHK}, respectively. Assume that there is a per-period fixed cost FC_{jt} of adopting ACH technology. Importantly, this is a per-period cost, not a one time sunk cost of adoption. As such, there are no dynamic optimization issues and firms simply maximize per-period profits[2].

Banks compare profits from adopting ACH to profits not adopting ACH. This difference is:

(6) $$\Pi_{jt} = T_{jt}^{ACH}\left[\left(p_{jt}^{ACH} - mc_{jt}^{ACH}\right) - \left(p_{jt}^{CHK} - mc_{jt}^{CHK}\right)\right] - FC_{it}$$

[2] There is some evidence of this nature of fixed costs in our data as we see a number of banks switching from adoption to non-adoption between periods. See GS for details.

i.e. the increment in profits from adopting is the number of ACH transactions times the difference in margins, minus the fixed cost of adoption. In empirical work we allow FC_{jt} to vary across firms as:

(7) $$FC_{jt} = \phi + \alpha_{jt}$$

where ϕ is a parameter to estimate and α_{jt} is an econometric unobservable that we assume is normally distributed. We allow α_{jt} to be both correlated across time for a given firm and to be correlated among firms in a given market; specifically, we let

(8) $$\alpha_{jt} = \alpha'_{jt} + \alpha''_{j} + \alpha'''_{m}$$

where 'm' indexes markets, $\alpha'_{jt} \sim \text{iid } N(0,1)$,[3] $\alpha''_{j} \sim \text{iid } N\left(0, \sigma^2_{\alpha''}\right)$, $\alpha'''_{m} \sim \text{iid } N\left(0, \sigma^2_{\alpha'''}\right)$ and where α', α'' and α''' are all independent from each other. In some specifications, we also allow for the market specific shock to vary across time, i.e. we add a fourth unobservable $\overline{\alpha}_{mt} \sim \text{iid } N\left(0, \sigma^2_{\overline{\alpha}}\right)$

Bank j will adopt ACH at time t if and only if $\Pi_{jt} > 0$. From (6), we can see that adoption will depend on other banks' decisions through T^{ACH}_{jt}, which is a function of u1 and u2. An equilibrium $\left(A_{1t} \ldots, A_{JT}, T^{ACH}_{1t}, \ldots, T^{ACH}_{Jt}\right)$ requires that all banks' adoption decisions are optimal conditional on all other banks adoption decisions, i.e.

(9) $$A_{jt} = \left\{\Pi_{jt}\left(T^{ACH}_{jt}\left(A_{1t}, \ldots A_{j-1,t}, 1, A_{j+1,t}, \ldots, A_{Jt}\right)\right) > 0\right\} \qquad \forall j$$

where $T^{ACH}_{jt} = P_{jt}\left(A_{1t}, \ldots\ldots, A_{Jt}\right) T_{jt}$ and where $\left(P_{jt}, u1_t, u2_t\right)$ jointly satisfy (2) and (3).

There are often multiple equilibria of this network adoption game. To see this, note that on one hand, if every bank is using the network good, then any one bank is likely to want to use it. On the other hand, if no bank is using it, then that one bank is likely to not want to use it.

[3] As adoption is a discrete decision, the variance of 1 is a normalization.

These multiple equilibria can be manifested both at the bank level, with multiple solutions to (9) given a unique conditional solution to (3), and at the individual level, with multiple solutions to (3).

This type of game generally has two stable Nash equilibria. Moreover, we can show that there is one stable Nash equilibrium that Pareto dominates all other Nash equilibria, and one stable Nash equilibrium (not necessarily distinct from the other one) that is Pareto inferior to all other Nash equilibria.[4] The reason for this result is that the network externality is assumed to be positive and so there is no trade-off from having more people join. Even more usefully, the proof provides an iterative mapping that helps compute these Nash equilibria very quickly.

We want to estimate a specification that is consistent with the presence of multiple equilibria, and that can allow us to estimate whether the world is in a good equilibrium or bad equilibrium. We are not aware of any economic theories that can predict the choice of equilibrium. Hence, we model the choice of equilibrium in reduced form: we assume that the world is characterized by some frequency θ of best equilibrium and 1-θ of worst equilibrium, where θ is a parameter we estimate.[5] We allow the equilibrium selection frequency to be correlated across time periods within a given network. To formalize, let $\omega_{mt} \sim \text{iid U}(0,1)$ and $\omega_m \sim \text{iid U}(0,1)$ denote a network-time and network specific random variable for equilibrium selection. Then, the market will be in the Pareto best equilibrium if and only if $\sigma_\omega \omega_{mt} + (1-\sigma_\omega)\omega_m < \theta$, where σ_ω is a parameter to estimate.

3. Data

Our principal data set is the Federal Reserve's billing data that provides information on individual financial institutions that processed their ACH payments through Federal Reserve

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[4] See GS for further discussion and a proof.

[5] Our method of estimating models with multiple equilibria is similar to the method used by Moro (2000) who treats the equilibrium choice as a parameter.

Banks.[6] We observe monthly data for the period of April 1995 through December 1997 and we aggregate these data to the quarterly level. We have two data sets: one lists the billing information for transaction originations, and the other lists the billing information for transaction receipts. ACH transactions can be one of two types: credit or debit. A credit transaction is initiated by the payer; for instance, direct deposit of payroll is originated by the employer's bank, which transfers the money to the employee's bank account. A debit transaction is originated by the payee; for example, utility bill payments are originated by the utility's bank, which initiates the payment from the customer's bank account. For each financial institution in the data set, we have the ACH volume processed through the Federal Reserve each month and the total amount that the Federal Reserve charged for processing that volume. We also have the American Banking Association (ABA) number that allows us to link this data with other publicly available banking data.

Financial institutions can adopt ACH as either originators or recipients or both. We assume that a bank has adopted ACH as an originator (recipient) in a given quarter if it originated (received) at least one ACH transaction.

The Federal Reserve is currently the dominant provider of ACH services. The Federal Reserve handled approximately 75 percent of the roughly 3.3 billion on-others commercial ACH transactions processed in 1996 and approximately 70 percent in 1998.[7] The remaining share of the on-others market is handled by three private sector ACH providers: Visa, Electronic Payments Network (formerly New York Automated Clearing House), and American Clearing House (formerly Arizona Clearing House). There are some network linkages between the different ACH providers. For instance, the Federal Reserve processes ACH items originated by members of the private networks and vice versa. However, for lack of data, we deal only with ACH transactions that are billed through the Federal Reserve, and treat Federal Reserve ACH as the relevant network for the good.

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[6] We thank the Federal Reserve's Retail Payments Product Office for making this data set available to us.

[7] NACHA and Federal Reserve estimates. Government transactions constituted another 600 million.

In addition to the ACH billing data, we use a number of publicly available databases to augment our data. First, we linked the Federal Reserve data with the quarterly Call Reports database. The Call Reports database provides information on bank assets, deposits, name, and the zip code of the headquarters for all banks that are registered with the Federal Deposit Insurance Corporation (FDIC). Several banks opened and closed during our sample period. We kept these banks in the sample for the quarters in which they were open.

One data problem that we encountered is that a large fraction of the American Bankers' Association (ABA) numbers—an identifier in the ACH billing data collected by the Federal Reserve—were not in the Call Reports database. Most of the ABA numbers that did not match are credit unions or thrifts.

The Call Report data on assets and deposits are reported by FDIC certificate number. Banks with a given FDIC certificate number may use one or more ABA identifiers when billing the Federal Reserve for ACH services. Thus, we aggregated the Federal Reserve ACH volume up to the FDIC number level. We then excluded all banks with assets of less than $10 million (percentage?) for all months in the sample and all remaining credit unions. We were left with approximately 11,000 banks over the 11-quarter sample period.

We identify network externalities in our model by examining correlations in usage for banks that are geographically close. Thus, we needed to find the distance between zip codes. We used the Census Tiger database to find the latitude and longitude of zip code centroids, and used the standard great circle formula to find the distance between centroids.

Our estimation procedure is based on the assumption that a bank's network is geographically local. Specifically, we assume that a bank directly cares about usage for ACH for other banks whose headquarters are within 30 kilometers of the headquarters of the given bank. Because we are solving for a simultaneous moves Nash equilibrium, the network that the bank is in is potentially larger. We need to also include all the banks that are within 30 kilometers of the banks that are within 30 kilometers, and all the banks that are near these banks, etc. We performed this process in order to separate our data set of 11,000 banks into mutually exclusive networks. Each network is self-contained, in the sense that every bank that is within 30

kilometers of any bank in the network is also in the network, and no bank in the network is within 30 kilometers of any other bank.

One significant data problem is that many banks have become national in scope. As the relevant network for these banks is likely to be national, our model would not be particularly meaningful for these banks. Thus, we kept in our sample only banks that are in small markets. Specifically, we kept all networks with 10 or less banks total during every time period of our sample. We were left with a sample of approximately 1,000 mutually exclusive networks with a total of approximately 2,000 banks over the sample period.

Table 1 gives some specifics on the networks, broken down by network size. Approximately half the networks in our sample – 4739 in all – are composed of only one bank. Another quarter of the networks have two banks. However, there are large numbers of networks with up to 10 banks. By excluding networks with more than 10 banks, we are excluding 567 networks, mostly larger banks. Banks in our sample tend to be smaller in terms of assets than average, and this is particularly true for networks with 5 or fewer banks. The percentage of firms using ACH appears to be quite consistent across network size, although banks in smaller networks have fewer ACH transactions. Table 2 gives some specifics on ACH usage over time. We can see that over time, the fraction of banks using ACH has increased. Moreover, there appears to be a large fraction of networks where every bank uses ACH – more than one would expect without correlations in usage.

One factor that can affect usage of ACH is its price. Prices that the Federal Reserve charges banks for ACH processing are set at a fixed rate and adjusted periodically. Figure 1 displays a time series of these prices. Note that the intraregional per-item prices (that is, prices for ACH items exchanged between banks located within the same Federal Reserve District) did not change throughout our sample period. At the same time, the interregional prices declined from $0.014 in 1995 to $0.01 in 1997. In May 1997, the Federal Reserve implemented a two-tier price system of $0.009 for banks with less than 2500 transactions per file and $0.007 for banks with more than 2500 transactions per file. We ignore the $0.007 price because we do not have data on number of transactions per file (only monthly totals) and because most of the banks in

our sample are sufficiently small as to only pay the higher rate. Because prices are set by fiat and do not respond to changes in local demand, they may be viewed as exogenous. We do not have any information on the prices that banks charge to their customers. In addition to per-transaction costs, banks must file fees of $1.75 per small file and $6.75 per file per large file and pay an ACH participation fee of $25 per month. Also, banks that offer ACH generally maintain a Fedline connection for ACH as well as other electronic payment services.

4. Estimation

Our model is based on a vector of unknown parameters $\left(\lambda, \beta_{\_}, \theta, \phi, \sigma_{\_}^2\right)$ and econometric unobservables $(\alpha, \varepsilon, \omega)$. The unknown parameters specify the functional form for the demand for ACH transactions, the mean fixed cost of entry, equilibrium selection rule and the variances of the econometric unobservables. The unobservables specify the unobserved components of the fixed cost of ACH provision and of the total number of transactions. For ease of notation, let us group the unknown parameters together as Ω and the unobservables together as υ. Our estimation algorithm seeks to recover Ω from the data. In this section, we describe our estimation algorithm(including the computation of equilibria) and explain how parameters of the model are identified.

4.1 Estimation Algorithm

Let us start by analyzing a given market in a given time period. Our data contain observed predetermined variables, namely assets x_{jt}, price p_t and time t, and observed endogenous variables, namely A_{jt} and T_{jt}^{ACH}. Consider a given parameter vector Ω'. For this parameter vector, densities for econometric unobservables υ are defined and it is possible to simulate the unobservables for the market at that time period. Given a vector of simulation

draws, we can easily compute the appropriate Nash equilibrium[8] of the industry in order to recover the endogenous variables. Details on the computation of the Nash equilibrium are provided in Section 4.2.

A natural way to estimate the model would be to construct the likelihood function for market m:

$$(10) \qquad L_m(\Omega') = P\left(\left\{A_{1t}, \ldots\ldots, A_{Jt}, T_{t1}^{ACH}, \ldots\ldots, T_{Jt}^{ACH}\right\}_{t=1}^{T} \middle| \left\{x_{1t}, \ldots\ldots, x_{Jt}, t, p_t\right\}_{t=1}^{T}; \Omega'\right)$$

Since actions by banks within a market are simultaneously determined via a Nash equilibrium, (10) specifies the likelihood for an entire market over the time period it is observed. We treat the market as the unit of observation, and assume that the observable and unobservable characteristics of different markets are drawn independently[9]. We need to consider the joint probability over time since there are unobservables that are correlated over time. In theory, one could compute this likelihood by integrating out the predicted Nash equilibrium values of the endogenous variables over the set of unobservables. In order to do this, we would have to solve use equilibrium behavior to predict the joint density function of the endogenous variables conditional on parameters and the exogenous variables. For each market, we could then evaluate this density at the observed value of the endogenous variables.

The problem with this method is that there is no closed-form solution for the density of the endogenous variables used in (10). While it is relatively easy to evaluate the equilibrium conditional on the unobservables, this density can only be evaluated by numerical integration of Nash equilibrium behavior over the unobservables. This suggests the use of simulation methods. Many recent papers use simulated maximum likelihood methods to estimate structural models.[10] However, the observed decisions in these papers are typically discrete (e.g. replace a bus engine or not; go to school or work). In our case, we observe the continuous variable of the number of

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[8] Appropriate means Pareto-best or –worst depending on ω_t.

[9] Because we allow for correlation across time in the unobservables, our unit of observation will actually be one market over time. However, here we exposit one market as the unit of observation, because it shortens the notation.

ACH transactions, T_{jt}^{ACH}. Simulation methods can easily be used to evaluate a discrete probability, but it is much more problematic, both numerically and theoretically, to use them to evaluate the density of a continuous random variable.

We pursue an alternative approach, method of simulated moments (MSM). To illustrate the MSM approach, suppose that we have S simulation draws, and define $\upsilon_s, s = 1, \ldots, S$ to be one simulation draw; each simulation draw υ_s specifies $(\alpha, \varepsilon, \omega)$ for every market. With MSM, we simulate the equilibrium for a vector of unobservables, and then find moments of the form:

$$(11) \qquad G(\Omega) = \sum_i \left(y_i - E\left[y_i(\Omega)\middle|\Omega\right]\right) \approx \sum_i \left(y_i - \frac{1}{S}\sum_s \hat{y}_{is}(\Omega)\right),$$

where y_i is any function of the data evaluated for market m across all time periods, and $E\left[y_i(\Omega)\middle|\Omega\right]$ is the expected value of that function in the equilibrium. We consider one market across time as one observation because our model includes random effects that persist over time. The MSM estimator minimizes the norm of (11),

$$(12) \qquad \hat{\Omega}_{MSM} = \arg\min_{\Omega} \left\| G(\Omega) \right\|.$$

McFadden (1989) and Pakes and Pollard (1989) show that one can substitute the mean of unbiased simulation draws $\frac{1}{S}\sum_s \hat{y}_{is}(\Omega)$ for their expectation $E\left[y_i(\Omega)\middle|\Omega\right]$ in (11) and still obtain consistent estimates even for a fixed number of simulation draws. The logic is that the errors between the simulated estimate and the true expectation will integrate out over markets.

While the MSM estimator is consistent, there are two central problems that arise using it in the context of our model. First, there are far too many moments to match. Our model contains

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[10] See Keane and Wolpin or Rust (1987) for instance.

several endogenous variables: up to 10 adoption and usage decisions per market per time period. All of these moment conditions should also be interacted with the predetermined variables to impose the conditional independence restrictions. Even more importantly, as we will infer network externalities from correlations in usage decisions, we would need to capture second- and higher-order cross moments; i.e. the usage of bank 7 times the usage of bank 10 minus the expected value of this variable. There are 210 second moments for the adoption decision alone (even neglecting correlation across time) . We cannot possibly match all these moments, because there would be a huge finite-sample bias, and it would be far too unwieldy. Thus, it would be extremely difficult to impose the essential restrictions of our model in MSM estimation.

To address this problem, we use a variant of the MSM estimator called indirect inference (II),proposed by Gouriéroux, Monfort and Renault (1993). We illustrate the computation of the II estimator for the case of one simulation draw. First, we perform some estimation routine on the true data, resulting in some parameter vector μ^{DATA}. The estimation is incorrect in the sense that the estimated coefficients in the inference do not correspond to any structural parameters. Examples for our model would be a bank-level regression of usage on exogenous variables in the model or a bank-level regression of usage on the (endogenous) usage decisions of other firms in the network. Second, for a given structural parameter vector Ω' and simulation draw υ_s, we compute the equilibria of the model for each market, and perform the same 'incorrect' estimation. Call the resulting parameter vector $\mu_s^{\Omega'}$. Then, the II estimator is constructed as:

$$(13) \qquad \hat{\Omega}_{II} = \arg\min_{\Omega} \left\| \mu^{DATA} - \sum_{s=1}^{S} \mu_s^{\Omega} \right\| \equiv \arg\min_{\Omega} \left\| G(\Omega) \right\|.$$

Thus, the II algorithm chooses the structural parameter vector for which the coefficients from the indirect inference most closely match the coefficients from the data. With the II algorithm, one can sensibly match many fewer moments. For instance, instead of 210 second moments interacted with each of the exogenous variables, we can perform a regression of the usage

decision on the usage decisions of other firms in the network and on assets. This will capture the same insight as the standard MSM estimator, that with network externalities, usage levels for banks in a network should be correlated.[11] Also, note that even though the II estimator in (13) is not linear in each observation (as is (11)), Gouriéroux, Monfort and Renault (1993) show that the estimator will still be consistent for a fixed number of simulation draws. The result follows because the estimate for one simulation draw, μ_s^Ω will converge in probability to $E[\mu^\Omega]$ as the number of observations becomes large. In Section 4.3, we motivate the exact choice of moments that we use in our II procedure.

There is a second problem with all MSM procedures, including the II variant. There are infinitely many differee

where $G_i(\cdot)$ is the moment condition for a particular market over all time periods. While this method will, in principle, provide asymptotically efficient estimates, there is a practical problem: the first-stage estimates often vary wildly depending on the weighting matrix used. This results in a huge variation in the second-stage weighting matrix and resulting huge variation in the final estimates. Thus, this is not just an econometric quibble, but a significant empirical problem.

We address this second problem by deriving the weighting matrix from the data rather than from the estimated values. Rather than using the standard weighting matrix (15), we use:

$$(16) \qquad A = \left(\mathrm{Var}\left[\mu^{DATA}\right]\right)^{-1}.$$

As (16) does not depend on a parameter value Ω, it will not be beset with the problems inherent in using the standard weighting matrix. Using (16), there is also no need to perform a two-stage estimation process.

As μ^{DATA} is not a linear function of individual observations, 'μ_i^{DATA}' does not exist, and we cannot calculate (16) in the same way as (15). Moreover, even though μ^{DATA} is composed of regressions, we cannot use the standard OLS variance/covariance matrix, because the regression is incorrect. In our case, the incorrectness is manifested by the fact that the regression unit of observation is a bank, instead of a market over time, and by the fact that we include endogenous regressors. In addition, since we run multiple reduced form estimations for our indirect inference, OLS variance/covariance matrices do not give us covariances between coefficients across the regressions. To address these issues, we use bootstrap methods. We resample the data with replacement, and calculate μ^{DATA} for 3,000 resampled data sets in order to numerically approximate its variance. To consistently resample given that we allow for random effects that link observations across time, our unit of observation for the sampling process is one network over time.

Using (16) and (13), we can compute the estimator $\hat{\Omega}_{II}$. To perform inference, we need to find the variance of the estimator. For robustness, we again use a bootstrap procedure to perform inference. For this bootstrap process, we again resample the data and econometric unobservables and recompute the estimates. Note that we resample from the original simulation draws in the same way that we resample from the original data. We repeat this process 100 times to obtain an empirical density of our estimated parameters.

4.2 Computation of Equilibrium

Recall that in order to estimate the parameters, we need to solve for the Nash equilibrium of the model conditional on a vector of pre-determined variables and econometric unobservables. Additionally, depending on the realization of ω_i, we need to solve for the Pareto-best or -worst equilibrium for a given market at a given time.

In general, estimation of Nash equilibria can be very computationally intensive. This computational intensity is a large part of the reason why structural models are notoriously difficult to estimate. In our case, it is actually computationally simple to solve for both Nash equilibria. The underlying reason for this is that the network externality is assumed to always be positive. Because of this, the optimal reaction functions will always be a monotone mapping of the previous stage reaction functions. This is also the basis of the proof that there is a Pareto-best Nash equilibrium given in GS, Proposition 1.

That proof constructs a Pareto-best Nash equilibrium by using the following iterative process on adoption and usage decisions for each bank. Start the first iteration by assuming that everyone is always using ACH, i.e. $\left(A_{1t}^{1}=1,\ldots,A_{Jt}^{1}=1\right)$ and $\left(P_{1t}^{1}=1,\ldots,P_{Jt}^{1}=1\right)$. Then, construct the second iteration by finding the usage decisions and probability of ACH transactions for each bank, given that banks are using ACH at the level given in the first iteration. This gives a vector $\left(A_{1t}^{2},\ldots,A_{Jt}^{2},P_{1t}^{2},\ldots,P_{Jt}^{2}\right)$ where each level is weakly less than in the first iteration. Repeat this process until convergence; convergence is guaranteed by this monotonicity property. GS show

that the limiting values $\left(A^N_{1t},\ldots,A^N_{Jt},P^N_{1t},\ldots,P^N_{Jt}\right)$ form a Pareto-best Nash equilibrium. Correspondingly, if we start the first iteration by assuming that no one is using ACH, i.e. $\left(A^1_{1t}=0,\ldots,A^1_{Jt}=0\right)$ and $\left(P^1_{1t}=0,\ldots,P^1_{Jt}=0\right)$ and then iterate to convergence, the algorithm will converge the Pareto-worst Nash equilibrium.

The only detail about this process that we have not stated is how to update the values of u1 and u2, which is necessary in order to find the probability of ACH transactions and usage decisions. The basic method of constructing these variables is to use their definition, given in (4). However, there are two details that bear mentioning.

First, customers choose their transaction decisions following the adoption decisions of banks. Hence, when deciding whether or not to adopt ACH, the bank can assume that its consumers will know that it has adopted. For our purposes, this means that we should always set A_j to 1 in the reaction function calculation for bank j. Note that other banks still perceive the true value of A_j in their reaction function calculation, because it is a simultaneous move game.

Second, recall from Section 3 that we define a network as the full area for which banks' strategies are mutually dependent, in Nash equilibrium. However, in our model, we assume that other banks' decisions directly enter into ACH transaction probability function only if the other banks are located within 30 kilometers. The impact of this assumption is that a bank's ACH usage will only reflect the usage decisions for banks within 30 kilometers of it, not for all banks in its network. We consistently address this issue by keeping track of which banks within a network are within 30 kilometers of other banks. Note that even though the strategies of banks that are further away does not directly affect the ACH transactions at a bank , the actions will be correlated through the Nash equilibrium.

Because of the monotonicity of the reaction functions, our algorithm converges to the appropriate Nash equilibrium very quickly. For instance, to evaluate one parameter iteration with 10 simulation draws, we require computing a Nash equilibrium for the roughly 1000 markets over 10 time periods with 10 different simulation draws. It takes about 2 seconds to solve for

these 100,000 equilibria on a modern workstation. This quickness permits us to perform very exhaustive numerical searches and to use bootstrap methods for more robust inference.

4.3 Identification and Choice of Moments

In this subsection, we discuss the exact choice of moments that we match, and explain how they affect the identification of the parameters. Recall that because we use II, our moment conditions are the differences in the coefficients of the indirect inference estimation procedure on the data and the same indirect inference estimation on the simulated equilibrium. Thus, it suffices to describe these estimations; we index the II coefficients by γ. There are two sets of parameters that we are principally interested in identifying. The first set is the network benefit parameters, β_1 and β_2 and the second set is the equilibrium selection parameter θ. Potentially confounding these are parameters on the variances of econometric unobservables including random effects, and on exogenous variables. We will explain how the different reduced form estimates should identify these parameters.

For our indirect inference, we estimate four regressions, and also match the moments of two endogenous variables and error terms from the regressions. We perform two regressions of usage decisions on the usage decisions for other banks in the network and exogenous variables, i.e.

$$(17)\qquad \begin{aligned} T_{jt}^{ACH} &= \gamma_1 + \gamma_2 x_{jt} + \gamma_3 x_{jt}^2 + \gamma_4 p_t + \gamma_5 t + \gamma_6 y1_{jt} + \gamma_7 y2_{jt} \\ A_{jt} &= \gamma_8 + \gamma_9 x_{jt} + \gamma_{10} x_{jt}^2 + \gamma_{11} p_t + \gamma_{12} t + \gamma_{13} y1_{jt} + \gamma_{14} y2_{jt} \end{aligned},$$

where x is assets as defined previously, and y1 and y2 are three variables that characterize the usage of the other firms in the network. Specifically, y1 is the asset-weighted fraction of other firms within the 30 kilometer radius that have adopted ACH, and y2 is the total number of ACH transactions by other firms in the radius divided by their total assets. Both variables are 1 if the

bank is the only bank in its network. Note that the definitions of y1 and y2 differ slightly from the definitions of u1 and u2 in (4). The reason for this is that the u's include the regressors themselves on the right-side, while the y's exclude the own bank's decision in order to make the estimates more stable. Note that the above regressions are linear reduced form analogs of the structural equations of our model.

We also perform two regressions where the right hand side variables are the exogenous characteristics of the market:

$$
\begin{aligned}
&T_{jt}^{ACH} = \gamma_{15} + \gamma_{16} x_{jt} + \gamma_{17} x_{jt}^2 + \gamma_{18} p_t + \gamma_{19} t + \gamma_{20} N1_{jt} + \\
&\gamma_{21} N2_{jt} + \gamma_{22} N3_{jt} + \gamma_{23} N4_{jt} + \gamma_{24} N5_{jt} + \gamma_{25} N6_{jt} \\
&A_{jt} = \gamma_{26} + \gamma_{27} x_{jt} + \gamma_{28} x_{jt}^2 + \gamma_{29} p_t + \gamma_{30} t + \gamma_{31} N1_{jt} + \\
&\gamma_{32} N2_{jt} + \gamma_{33} N3_{jt} + \gamma_{34} N4_{jt} + \gamma_{35} N5_{jt} + \gamma_{36} N6_{jt}
\end{aligned}
\quad . \tag{18}
$$

In (18), N1,…,N6 are parameters measuring exogenous characteristics about the network. Specifically, N1 is the total assets of all banks in the network (including those further than 30 kilometers), N2 is the sum of squared assets of all the banks, N3 is the square of the sum of assets of all the banks, N4 is the total assets of all banks within 30 kilometers, N5 is the number of banks within 30 kilometers and N6 is the 30 kilometer Hirschmann-Herfindahl Index (HHI). These regressions are intended to represent a (simultaneous equation type) reduced form of our model where equilibrium adoption and usage decisions are a function of all the exogenous variables in the market.

In addition to these 36 moments, we match 16 other moments. These include three moments of both the network level usage and adoption, T_{jt}^{ACH} and A_{jt}, and the four standard deviations of the estimated residuals from (17) and (18).

Finally, we match six random effects terms, in order to capture the correlation across time in our econometric unobservables. Specifically, we match the between-bank, between-market-across-time and between-market-specific-time variances of the error terms for the transaction equations in (17) and (18). Specifically, the between-bank variance is:

(19) $$\gamma_{47} = \sum_m \sum_j \left(\left(\frac{1}{T_j} \sum_t e_{jmt} \right)^2 \right),$$

where e_{jmt} is the residual from the transaction regression in (17) or (18). Note that we have used the index T_j and left out the superscripts from the summations because we do not have a balanced panel. Correspondingly, the between-market-across-time variance is:

(20) $$\gamma_{48} = \sum_m \left(\left(\frac{1}{T_j} \sum_j \sum_t e_{jmt} \right)^2 \right)$$

while the between-market-specific-time variance is:

(21) $$\gamma_{51} = \sum_m \sum_t \left(\left(\frac{1}{J} \sum_j e_{jmt} \right)^2 \right).$$

Equation (21) is particularly important because it will help identify the random effect $\overline{\alpha}_{mt}$ that is constant for a given market at a given time period, that we include in some specifications.

There are two separate sources of identification that we seek to capture with our model and these moments. The first source of identification is the correlation effect; the second source is the excluded variables effect. We now detail how both of them will identify the network effect parameters β_1 and β_2.

First is the idea that if there are network effects, then usage decisions for banks within a network will be correlated. This forms the basis of the test for network effects in GS. This is why we use regression (17). Changes in the structural network effect should result in changes in the coefficients on the y's in our reduced form regressions. We also want to separate network effects

from regional or bank-level correlations in preferences. This is why we include a random effect in the structural model, which should be identified off the between correlation in (19). Network effects are indicated if increases in usage for banks are correlated given these random effects. Additionally, we include price and a time trend to separate out the effect of increased usage over time due to increased technological acceptance and lower costs and prices.

Our second source of identification comes from the natural exclusions from the ACH usage and adoption decisions (3) and (6). Specifically, we assume that the exogenous characteristics of other banks can be excluded from the profit function of a given bank. For example, if bank B becomes larger, this does not directly enter into A's profit function, but in equilibrium does result in a higher ACH usage by the merged firm and hence by bank A. Excluded exogenous variables provide a natural instrument for the included endogenous usage levels of other banks. This forms the basis for the test for externalities in GS. In our indirect inference procedure, this instrumental variable identification is captured in the N2,…,N5 variables in (18). Note that N2 and N5 in particular are measures of market concentration. We could potentially apply just this identification in a straight instrumental variables estimator. Two problems would arise: first, T_{jt}^{ACH} has an mixed discrete/continuous structure, which we can model directly, but which is hard to estimate with instrumental variables. Second, the observations are not iid, since different banks within a network have correlated usage levels. Thus, the standard IV inference would be incorrect.

Note that in the estimation runs where we allow market-specific random effects to vary across time, we will principally be identifying the network effects via the excluded variables effect, i.e. from within-market changes in exogenous variables, such as bank mergers, closing or openings. Similarly, we estimate specifications where identification comes primarily from the covariance restriction, i.e. that the market specific random effects do not change over time.

It is also useful to understand how the equilibrium selection parameters $(\theta, \sigma_{\omega})$ will be identified. These parameters will be identified by differences in usage given different industry structures. For instance, as the number of firms increases, the increasing externality will cause

there to be more likely to be a Pareto-worst equilibrium that is different from the Pareto-best equilibrium. Thus, we will be able to identify the equilibrium selection parameters by examining whether there is increased unexplained variance in behavior for networks with more than one bank that does not exist for networks with one bank. Note that if we saw a high variance in the usage levels in all markets, this could be evidence of high fixed costs, and not necessarily of multiple equilibria.

Because there are two overlapping sources of identification, it will be useful to examine how much each of these sources will affect the parameter estimates to examine how robust our conclusions are. In Section 5.2, we selectively eliminate both of the sources of identification, and examine how the results differ.

5. Results and Implications

Using the indirect inference algorithm developed in Section 4, we have estimated structural parameters, and found non-parametric standard errors, for our base model and various specifications. We first present our results, then analyze their implications and lastly perform robustness tests.

5.1 Base results

Table 3 gives base parameter values. We estimated the model with only one network effect (u2), setting u1 and u3 to 0. All of the parameters have the expected sign. The coefficient on price is negative and significant. The coefficient on time trend is positive, suggesting that there is increased acceptance of technological goods and that a portion of the network externality is from outside the 30 kilometer area of our model.

How bad is bad equilibrium. How good is good equilibrium.

We find that the network effect is positive and quite large.

Interestingly, the coefficient on equilibrium selection, θ, is estimated to be essentially 1. This suggests that the world is virtually always in a good equilibrium. Thus, it does not appear that we are stuck in a bad equilibrium.

Usage level in bad vs. good equilibrium.

Random effects size.

5.2 Implications

5.3 Robustness

Eliminate one of the two sources of identification. Examine how this affects the results.

6. Conclusions

In this paper, we have estimated an equilibrium model of network externalities for the ACH banking industry. We estimate the model via a method of simulated moments procedure, where the equilibrium predictions of the model are matched to the data. We seek to understand the magnitude of the network externalities and to what extent the world is trapped in a Pareto-inferior equilibrium. The parameters on network externalities and equilibrium selection can be identified by two sources: covariance restrictions and exclusion restrictions.

The parameter estimates suggest that the world is in the Pareto-superior equilibrium. Network externalities appear to be significant in magnitude.

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Table 1: Characteristics by Network Size

Number of firms in network	Number of networks	Mean assets by bank	Mean % of banks using ACH	Mean # of ACH transactions by bank
1	4739	90.2M	65.7%	1183
2	2633	96.6M	69.8%	2979
3	957	190M	66.6%	60,551
4	595	218M	69.5%	3916
5	304	300M	77.7%	16,560
6	221	1.45B	76.5%	60,313
7	140	545M	65.2%	32,553
8	144	243M	66.7%	5809
9	58	313M	65.6%	17,613
10	104	345M	66.7%	33,468
>10	567	626M	70.5%	41,152
All	10462	184M	67.9%	11,978

Table 2: Usage Over Time

Time periods are quarterly starting with April - June 1995.
Table includes networks with 2 or more banks.

Time Period	# of networks with no firm using ACH	# of networks with some, but not all, firms using ACH	# of networks with all firms using ACH
1	6.40%	76.1%	17.5%
2	5.74%	76.4%	17.9%
3	5.15%	79.0%	15.8%
4	2.80%	78.0%	19.2%
5	2.13%	77.0%	20.9%
6	2.85%	73.7%	23.5%
7	2.51%	73.4%	24.1%
8	2.54%	68.8%	28.6%
9	1.85%	67.2%	31.0%
10	1.87%	65.5%	32.6%
11	1.50%	66.4%	32.1%

Table 3: Parameter Estimates

Parameter	Value	Standard Error

Table 4

Fit of Model

Moment	Value in Data	Value in Simulated Equilibrium