Multimarket Contact, Competition, and Broadband Provider Entry

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Abstract

This work examines the relationship between multimarket contact and entry in the US broadband service industry. I examine a unique dataset on entry into ADSL broadband over the years 2005-2008 in the US. Unlike most previous studies, I do not assume that the measures of multimarket contact used as regressors are exogenous. Results indicate that multimarket contact increases the probability of entry into local broadband markets by incumbent local telephone companies, which is consistent with the firms' expectations that competition will be softer in such markets. Thus, the evidence is consistent with the notion that multimarket contact facilitates tacit collusion. A deeper investigation into the likely sources of the impact of multimarket contact on entry indicates that the Spheres of Influence story of Bernheim and Whinston (1990) is much more likely than their Transfer of Power story. This result indicates that heterogeneity among firms within markets may be a more important driver of competition (or its lack) than heterogeneity among markets. Some implications for policy toward the industry are discussed.

I. Introduction

Economists interested in the organization and competitive behavior of industries have long noted that multimarket contact (hereafter, "MMC") between competitors may facilitate tacit collusion and soften price competition.[1] MMC occurs when two or more firms meet in many geographic or product markets. Bernheim and Whinston (1990) show that the simplest story for why MMC facilitates collusion, that MMC gives a rivals more chances to retaliate against a firm deviating from collusion, is incorrect.[2] Instead, multimarket contact makes it easier to satify the incentive constraints for tacit collusion among firms, since the constraint for a firm need hold only in the aggregate, not in the individual markets. A sizeable empirical literature has grown over the years testing various hypotheses connected to MMC and market outcomes. Most studies conclude that MMC indeed leads to less aggressive competition among firms.[3] However, the empirical literature on MMC is deficient in two respects. Some previous studies treat MMC as exogenous, when in fact the expected nature of the rivalry postentry likely affected firms' entry decisions, which in turn create the MMC. Furthermore, Sorenson (2007) takes the empirical literature to task for not clearly linking the evidence to why MMC might matter. In particular, Bernheim and Whinston (1990) suggest two settings (int. al.) in which MMC facilitates collusion. The first occurs when firms are heterogeneous in cost within markets. If so, then MMC helps sustain a firm's strategy of dominating in its low-cost markets—developing a "sphere of influence" (SOI)—with the tacit acquiescence of its rivals, which do the same elsewhere. The second occurs when markets are heterogeneous in the degree of rivalry. In this case, MMC facilitates collusion by allowing the firms to transfer slack in the incentive compatibility condition for collusion from markets that are nonrivalrous to markets where collusion would otherwise break down. The latter case is termed "transfer of power" (TOP).

This paper explores data from the US broadband service market to explore the relationship between MMC and entry. The work contributes to the literature in three ways. First, while there are many studies looking at the impact of MMC on prices or profits, there are few studies on the impact of MMC on entry into markets. I explore how MMC relates to the decisions of incumbent telephone companies to offer ADSL broadband. Second, nearly all of the papers published on MMC and entry are outside the economics literature. Instead, they are from the management, strategy, or organizational ecology literatures, which (while interesting in their own right) typically ignore statistical issues that require attention if one claims to identify the causal impacts of MMC. For example, MMC is typically treated as exogenous when in fact severe endogeneity problems create the potential for bias in the statistical estimates.[4] I carefully examine the issue of endogeneity and (attempt to) correct for it. Third, there are unexplored hypotheses to test. In particular, most empirical investigations of MMC do not attempt to identify whether SOI or TOP (or another reason) is responsible for the noncompetitive market outcomes observed.

[1] See Bernheim and Whinston (1990) and their review of the literature.

[2] If firms and markets are identical, then meeting in multiple markets merely scales up the competitive considerations involved in a single market without altering the incentive constraint for tacit collusion.

[3] See the summary of the literature in Waldfogel and Wulf (2006), for example.

[4] This problem is pointed out by in Ciliberto and Williams (2012). Waldfogel and Wulf (2006) are also among the very few other papers acknowledge the endogeneity problem.

In additional to the interesting theoretical and econometric issues involved, there is also an important policy dimension to the present work. Federal antitrust agencies and state and federal regulatory commissions scrutinize conduct in the telecommunications and broadband industries. In recent years, concerns about competition in the US broadband service industry have been raised. When governmental agencies conduct market reviews, typically in the context of pending mergers such as the Verizon/ALLTEL merger in 2008 and the failed AT&T/T-Mobile merger attempt from 2011, they most often look at factors internal to the markets involved. Such internal market factors include the concentration of the providers, barriers to entry, the scale and elasticity of demand, and access to essential inputs such as spectrum or network backbone access. For example, in the Verizon/ALLTEL merger order, the FCC refers to its analysis as a "multi-factor, *market-specific* analysis" (emphasis added; FCC, 2008). It is less common to consider the impact of intermarket linkages, such as MMC, on competition. Even when the possibility of tacit collusion is examined (called "coordinated effects" in the parlance of antitrust), multimarket considerations are generally ignored. In fact, I am not aware of any decision written by the FCC, for example, that even alludes to the issue of MMC. Indeed, the US DOJ explicitly rejected one antitrust case where the argument for collusion rested on multimarket considerations.[5] However, if MMC indeed has significant effects on firm conduct, then it should also be explored in merger analysis and other antitrust actions.

The plan of the paper is as follows. A review of the literature and discussion of the issue involved is in the next section. In Section III I describe the data. I develop my empirical model and present results in section IV. The final section contains concluding discussion.

II. Literature Review and the Issues Involved

The early empirical literature in industrial organization on MMC examined data across manufacturing industries (Scott, 1982, 1991; Hughes and Oughton, 1993), showing that MMC increased the profitability of firms. Later studies honed the precision of the analysis by looking at specific industries: Heggestad and Rhoads (1978) and later authors for banking; Evans and Kessides (1994), Ciliberto and Williams (2012), and others for airlines; Fernandez and Marin (1998) for hotels; Fu (2003) for newspapers; and Jans and Rosenbaum (1997) for cement. Reviews of the MMC literature such as Jayachandran, Gimeno and Varadarajan (1999) and Korn and Baum (1999) note that such studies typically find that MMC is positively associated with price-cost margins or other quantities related to higher profits or less-competitive outcomes among firms.[6] To my knowledge, the role of MMC in broadband service markets has not yet been examined. Perhaps the closest related industry is telecommunications more broadly defined. Parker and Roller (1997) and Busse (2000) both examine MMC in the wireless telecommunications industry, and find association between MMC and higher prices. This naturally leads one to look for a role for MMC in other markets in which these (and other) firms meet and compete.

[5] Several foreign companies sought a case against F. Hoffman-LaRoche of Switzerland in a US federal court regarding price fixing in the vitamin market, even though the alleged conspiracy did not take place in the US. The plaintiffs argued that collusion in the US market led to equally high prices abroad due to demand linkages between markets. See Choi (2012).

[6] Due to publication bias, however, one should stop short of assuming that MMC heightens tacit collusion in "most" industries. It is natural to suspect that a study showing that MMC was apparently of no importance in an industry would be harder to publish than one finding strong linkages.

The empirical IO literature on MMC focuses on prices and profitability; for a look at entry one has to look at literatures from other disciplines.[7] Beginning with the seminal work of Baum and Korn (1996), researchers from various business disciplines other than economics began to look at MMC's impact on entry. Baum and Korn (1996) found that MMC lowered entry rates in California airlines markets. Haveman and Nonnemaker (2000) find an inverted U shape to the relationship between MMC and entry in banking, which Stephan et al (2003) also find for hospitals. Other studies in this vein include Fuentelsaz and Gómez (2006) for banking, and Kang, Bayus, & Balasubramanian (2010) for new product entry in the personal computer industry, and Alcantara and Mitsuhashi (2011) for auto parts. Several of the papers cited above look for and find an inverted U: when MMC is low, increases in MMC increase entry, but after a threshold level of MMC further increases in MMC deter entry. Usually without reference to formal economic modeling, these papers justify the nonmonotonic relationship as follows. To create the conditions for MMC to facilitate collusion, firms must enter each other's markets. However, once MMC and the attendant collusion are well established it deters aggressive actions by rivals, and entry is one of the deterred actions (Stephan et al., 2003).

Although it may bear more investigation, in the present version of the paper I do not look for nonmonotonicity in the effects of MMC on entry. This is for two reasons. First, in preliminary econometric work, I found no evidence of nonmonotonicity. Second, the broadband industry is not likely to consider entry by an incumbent telephone company to be an "aggressive action" that would disrupt an atmosphere of mutual forbearance among firms. Given the growing demand for broadband, offering ADSL or other forms of broadband was only a matter of timing for most of the incumbent wireline firms. A truly aggressive action in this industry would be to invade the service territories of other ILECs, which the major telephone companies have largely chosen not to do.

I also do not adopt the econometric methodology of the entry literature. Some of these papers, such as Haveman and Nonnemaker (2000), use hazard rate models for entry, treating the time until a firm enters a market as a duration. Others (e.g., Stephan et al., 2003) use a logit model for entry, which is essentially a discrete-time duration model for the time until entry (Sueyoshi, 1995). A key thing to note about these approaches is that the dependent variable for entry is defined as *new* entry into a market. Thus, after entry occurs nothing else is modeled.[8] This is in contrast to the empirical IO literature on entry in general, where the dependent variable is the firm's presence in a market (or the count of firms present).[9] The key insight from the work of Bresnahan and Reiss (1987) and others is that observing a firm both entering *and remaining* in a market can lead to inference about the profitability of the market. My approach here relies heavily on this fact, for while I do not observe margins (or even prices) in the local markets, I assume that entry is driven by the expectation of what those margins will be.

Another feature of the existing empirical literature on MMC is that the key variables measuring MMC are typically treated as exogenous. With some recent exception in the economics literature, notably Ciliberto and Williams (2012) and Waldfogel and Wulf (2006), the likely endogeneity of the measure of

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[7] This is not to say that some theory papers in IO don't address MMC and entry; see Chen & Ross (2007) and Seabright (1996) for two of the few examples.
[8] But see Baum and Korn (1996), who after entry also model the probability of failure and exit.
[9] Alcantara and Mitsuhashi (2011) also take this approach in their study of MMC and entry.

MMC is ignored. It is not hard to see why MMC is likely to be endogenous. For example, if a positive demand shock attracts large firms to a market, MMC will naturally rise. Thus entry and MMC will exhibit spurious positive correlation driven by unobserved heterogeneity across markets instead of by causal factors.[10] Thus, I carefully develop empirical models designed to avoid the endogeneity problem. Parenthetically, this is another reason not to adopt the hazard rate modeling approach, where dealing with endogenous and co-evolving regressors is a much trickier problem.

III. Description of the Data

The data on broadband entry for the empirical investigation come from the US Federal Communications Commission (FCC) Form 477. The FCC has collected data from providers of end-user broadband service since 1999. All facilities based broadband providers in the US are required to complete the semi-annual Form 477, which until 2009 required them to list each five-digit ZIP code in which they provide service. The firms provide separate ZIP code lists for each type of wireless, wired, fixed, or mobile broadband service offered. Thus the number and identity of firms offering service of each type of broadband is known at the ZIP code level, although subscribership data are available only at the state level.[11] The period examined in the study is midyear 2005 to midyear 2008.[12] Previous investigation of these data revealed that there is a surprising amount of apparent entry and exit for a single period only, some of which may be due to filing errors (Prieger and Connolly, 2013). For this reason, I group the semi-annual filings into four periods, an initial baseline taken from the June 30, 2005 filing (Period 0), and subsequent periods grouping data from the December 31 and June 30 filings (see Table 1). If a firm was present in either the December or June filing for periods 1-3, it is treated as having entered (or remained in the market) that period.

Any study on entry must define the markets to be studied. From the household's perspective, the market consists of all broadband providers able to serve the household's location. The same is true for business subscribers. This argues for a narrow market definition. From the provider's perspective, however, the nature of broadband network infrastructure implies that "Swiss cheese" entry—offering service to one small group of locations but not others nearby in the same service footprint—is undesirable. Given the nature of the data, any geographical unit equal to or larger than a ZIP code can be chosen. The question of market definition is further complicated by the very different network technology involved among the various types of broadband. The natural unit of entry for digital subscriber line (DSL) service is the local telecommunications central office, the facility housing the switching equipment (the *wire center*).[13] In many suburban areas, the central office serving area and the

[10] Waldfogel and Wulf (2006) make this point in the context of price-cost margins instead of entry. Evans and Kessides appear to be the first to acknowledge the endogeneity problem; they control for endogeneity across markets (but not across market-periods) with fixed effects.

[11] The FCC does not publically release the data except in heavily censored form. This study makes use of the raw source data, which were provided under a confidentiality agreement. We therefore will not identify any of the providers by name in this study.

[12] The data before 2005 are not comparable, because the smallest providers were not required to file Form 477; the data after our period are not available to us under our agreement with the FCC.

[13] However, even after deploying broadband network equipment in the wire center, the provider may still need to improve the local loops on a street by street basis to enable DSL subscription. In many areas this had already been accomplished by 2005.

ZIP code roughly coincide, for a small to medium sized community is likely to have one of each. Cable modem service is offered out of the *head end*, the cable analog to a central office. Cable service head ends and serving areas in general are unrelated to telecom service areas, although again in the case of well-defined or isolated communities they may largely overlap. Wireless service, whether fixed or mobile, has service footprints that may bear no relation to either cable or DSL serving areas. Finally, satellite broadband is available from several providers to any location in the US with a clear view of the southern sky.

In the end, therefore, any geographic delineation of broadband markets for purposes of academic inquiry must be artificial and only an approximation of how the firms involved view their markets and competitors. The market definition I choose is the *ZCTA group*. The building block for a ZCTA group is the Zip Code Tabulation Area (ZCTA), an area defined by the US Census Bureau (in my case, for the 2000 Decennial Census) that generally is meant to coincide with a ZIP code.[14] Using ZCTAs allows linking the ZIP code data from the FCC to ZIP code and ZCTA data from other sources. However, in urban areas the ZCTAs tend to be quite small compared to (for example) central office serving areas. Therefore I aggregate some ZCTAs with other contiguous ZCTAs to form a group. I refer to both single ZCTA and multi-ZCTA markets as ZCTA groups, for simplicity.[15]

While it is straightforward to determine where any given broadband provider offers service using the FCC data, it is much more difficult to ascertain where the provider is a potential entrant. One could adopt a long-run perspective and count any firm offering broadband service anywhere in the US as a potential entrant into all markets. The dataset contains information on all types of broadband providers. However, in this version of the paper I take a shorter run perspective on entry, and focus on a subset of potential broadband providers whose likely areas of entry are readily determined: incumbent local exchange carriers (ILECs). The advantage of focusing on ILECs and their entry into the ADSL broadband market is that due to the nature of telecommunications regulation (or its legacy), we know where these firms offer telecommunications service.[16] In addition, ILEC broadband is reported separately in Form 477, so their entry is readily observable.[17] In this paper, I examine entry by ILECs into ADSL broadband in mainland US markets. Coverage is not quite complete, for I dropped markets

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[14] ZIP codes do not define areas, but inside consist of collections of addresses. ZIP codes, which are defined by the USPS, are constantly changing, whereas ZCTAs are stable (at least between decennial censuses).

[15] The aggregation procedure, briefly: I defined any ZCTA with area less than π square miles (corresponding to a radius of one mile if the area were circular) as "small" and in need of aggregation. When the wire center area (WCA) is less than 5 square miles, I group all ZCTAs in it (if it contains any small ones). For remaining small ZCTAs, I aggregated them to the WCA if the WCA is not too large (< 20 sq. miles) and at least 2/3 of ZCTAs in the WCA are small. For remaining small ZCTAs, I joined them to the nearest larger ZCTA unless the distance was suspiciously large. About 25 small ZCTAs remained, and I examined each visually to determine appropriate aggregation. All GIS work was performed in ArcMap 10.

[16] I took the location of all the wire centers in the US and the identities of the firms operating them from various filings of NECA Tariff No.4 for the period studied. The tariff lists V&H coordinates of the wire centers, which I converted to latitude and longitude for analysis in ArcMap. Matching the names of the operating companies listed in the tariff to the holding company names in Form 477 was more challenging, but most names were able to be matched after investigation into corporate organization.

[17] Technicality: an ILEC can offer broadband out of its home territory as a Competitive Local Exchange Carrier (CLEC), or even within its home territory in some states, due to regulatory distinctions. This would only be a problem for my firm, location, and broadband service matching if the practice of offering broadband in a market as a CLEC but not as an ILEC (by firms who are ILECs somewhere in the state) is common. However, it is rare: in only 7.9% of markets does an ILEC offer service as a CLEC alone. Since I also have complete location data for CLECs, I am able to count such cases as entry by the ILEC.

exhibiting discrepancies in the data.[18] The final data set comprises 475 ILECs potentially offering ADSL broadband in 42,962 market-periods (over 14,000 ZCTA groups in each of the three periods).

Other data from various sources are matched to each market for use as regressors. Demographic data for the ZCTAs come from GeoLytics. Counts of business establishments in the markets are taken from the US Census Bureau's *ZIP Business Patterns*. Geophysical land cover characteristics were calculated for the markets from NLCD data,[19] and elevation data were calculated from SRTM data,[20] to control for network deployment costs.

IV. Empirical Model and Results

A. Model

In this section, I describe how multimarket contact is measured, and introduce the empirical models.

1. Measuring multimarket contact

There are a multiplicity of measures of MMC found in the literature, including market, firm, and firm-market specific measures. The measures range from a simple count of markets where two firms meet to more nuanced measures involving weighting or averaging. I adapt the firm-market specific formulation of Baum and Korn (1996) for my primary measure of MMC. The measure, denoted MMC_{imts} in the equation to follow but just $MMC_{t,s}$ in the text for simplicity, relies on several fundamental notions. Let D_{imt} be a binary indicator variable for firm *i*'s presence in market *m* at period *t*. If *m* is not the focal market (i.e., the particular market firm *i* is considering entering), then D_{imt} measures actual entry. If *m* is the focal market, then for purposes of the calculations below $D_{imt} = 1$. Thus, the potential entrant into focal market *m* thinks about what MMC would be there *if* it entered, taking as given the actual entry decisions *i* has already made in all the nonfocal markets. This approach mimics the aspect of a firm's optimal entry strategy that no single-market deviation from the strategy is profitable, given the entry decisions in the strategy for other markets.

Let d_{js}^{it} be the number of markets in which firms *i* and *j* "meet," where firm *i*'s presence is at period *t* and *j*'s presence is at period *s*. Thus d_{jt}^{it} counts actual coincidence in markets, while d_{jt-1}^{it} counts the number of *expected* meetings between the two firms when *i* forms expectations about *j*'s entry decisions based on where *j* was last period. Formally, we have $d_{js}^{it} \equiv \sum_m (D_{ims} D_{jmt})$. Within a particular focal market *m*, let N_{ms}^{it} be the number of multimarket rivals that focal firm *i* would expect to meet there if *i* entered, where expectations about *j*'s market presence are formed from *j*'s market presence in period *s* (i.e., using D_{jms}). For inclusion in N_{ms}^{it}, a multimarket rival is defined as a firm that firm *i* expects

[18] I dropped markets in which an ILEC associated with the market based on the data from the NECA tariff did not offer broadband, but the data from Form 477 indicate that some ILEC did offer ADSL in the market. In such markets, it may well be the case that there are multiple ILECs serving parts of the area, some offering broadband and others not. However, the phenomenon may also be caused by mismatching company names between data sources, and to be safe I excluded such markets, which were about 10% of the total.
[19] National Land Cover Database 2006; see http://www.mrlc.gov/nlcd2006.php (Fry *et al.,* 2011).
[20] Shuttle Radar Topography Mission V4 (30m data). See http://srtm.csi.cgiar.org (Jarvis et al., 2008)

to meet in at least one other market besides m (i.e., a firm j for which $d_{jt}^{is} > 1$, where meeting in market m is treated as the first contact). With these quantities in hand, the expression for $MMC_{t,s}$ is:

$$MMC_{imts} = \begin{cases} \dfrac{\sum_{j \neq i} 1(d_{js}^{it} > 1) D_{jms} d_{js}^{it}}{N_{ms}^{it} \sum_m D_{imt}} & \text{if } N_{ms}^{it} > 0 \\ 0 & \text{if } N_{ms}^{it} = 0 \end{cases} \quad (1)$$

where $1(a)$ is the indicator function, taking value 1 if expression a is true and 0 otherwise. To see what $MMC_{t,s}$ is measuring, consider the case for $s = t$. Then the summand in the numerator is the number of markets in which i and a multimarket rival j meet. If j does not meet i anywhere outside of market m or is not present in m, the summand is zero. The numerator is the sum of such multimarket contacts over all other firms. The scale of the numerator is on the order of (# rivals) ×(# of markets). Since it is important to isolate the impact of MMC on a firm's behavior separately from impact of the scale of the firm, the terms in the denominator normalize $MMC_{t,t}$. The first term in the denominator by itself converts the measure to a count of multimarket contacts per multimarket rival met in m. The second term in the denominator, the number of markets in which firm i is present, completes the mapping of the measure to the [0,1] interval. Thus, $MMC_{t,t}$ is the fraction of the markets firm i is in where it meets its multimarket rivals from m, averaged over multimarket rivals in m.

When $s \neq t$, the interpretation of $MMC_{t,s}$ is the same as above, except that expected instead of actual contacts are used in the computation. For robustness checks, I also calculate a weighted version of $MMC_{t,s}$ where in the computation of d_{js}^{it} and $\sum_m D_{imt}$ in (1) each of the markets is weighted according to how many people and business establishments are in the market.[21]

2. The empirical model

The estimations (for now) consist of OLS, IV, and fixed effects panel data specifications. Other modeling choices are available, so here I will justify the particular choices made. Using OLS means adopting a linear probability model for the binary entry decision in each observation. While a logit or probit could also be used (and eventually will be for robustness checking), the marginal effects from probit and logit models are typically very similar to those from the linear probability model.[22] Using OLS also leads in a straightforward manner to the IV estimations that follow. While nonlinear IV, gmm, and MLE methods could be used to handle endogenous regressors in logit or probit models, linear IV methods are much more straightforward, the results are easier to interpret, and the computational burden is lighter.[23]

[21] The weights for a market are composed from a weighted count of households and business establishments in the ZCTA group, where the latter are multiplied by 2.6. The multiple was determined by comparing the actual number of business and residential lines for ADSL and cable modem service with the number of households and establishments in the US, June 2007, which showed that each business is 2.6 times more likely than a household to demand service.

[22] For a more formal defense of using the LPM over a nonlinear model, refer to Angrist (2001).

[23] The latter aspect is not that important in the present version of the paper, where I only consider entry by ILECs and have fewer than 50,000 observations. Once I expand the focus to include entry by CLECs and cable firms, however, the dataset grows to about three-quarters of a million observations.

Finally, using the linear probability model ensures that there is no incidental parameter problem when including fixed effects.[24]

Current practice in most of the literature in empirical industrial organization is to adopt structural econometric modeling of entry, based on the pioneering work of Bresnahan and Reiss (1987,1991) and Berry (1992) and others for static entry games and Pakes, Ostrovsky, and Berry (2007) and others for dynamic games. I do not adopt the structural approach here for several reasons. In static entry games with complete information, the fundamental multiplicity of equilibria leads to empirical models in which the number of firms—which is the same in all equilibria—is chosen for the dependent variable. Feasibly estimable models for the number of entrants in a market, however, require strong assumptions of homogeneity of the variable profit function among firms that are unlikely to hold in the broadband market I examine. The game theoretic model upon which the structural empirical specifications rest are also typically quite simple, and do not incorporate cross-market strategizing as would be necessary to investigate MMC.

The more recent literature in empirical dynamic entry games extends the simple assumptions of the static entry models, but at the cost of a greater computational burden than is affordable with this size dataset. A promising new approach from Bajari, Benkard, Levin (2007) gets around the computational burden of computing equilibrium by basing the estimations on each player's best response function. Bajari *et al.* (2010) adapt this approach to static entry games. While their approach greatly lowers the computational burden in a simple entry game, in my application the computational cost of computing expected MMC renders their method infeasible here.[25] For all of these reasons, therefore, I take a reduced form approach.

The empirical model used here is:

$$Y_{imt} = f(\text{market, firm and market-firm characteristics}) + \beta_1 E(MMC_{t,t}) + \beta_2 E(NR_{imt}) + \varepsilon_{imt} \qquad (2)$$

The dependent variable is binary and equals 1 if firm *i* is present in market *m* in period *t*, zero otherwise. $E(MMC_{t,t})$ is the multimarket contact that the firm expects if would face if it enters market *m*. I will consider various ways in which firms form expectations below. $E(NR_{imt})$ is the expected number of rivals (not necessarily multimarket rivals; multimarket considerations are accounted for in the previous term) the firm would face in market *m*. The error term may contain a market-, firm-, or firm-period-specific fixed or random effect as well as idiosyncratic error, depending on the specification used below.

[24] Probit fixed effects models are inconsistent because of the incidental parameters problem. Of course, using conditional logit also gets around the problem.

[25] Their method is a two-step procedure. In the first step, a reduced form mapping from market characteristics to the probability of firms' entry is estimated. In the second step, the structural parameters of the entry game are estimated, when the results from the first step are used to estimate the focal firm's expectations about the entry decisions of the other players. In my application, however, the entry expectations are not only about whether rival firm *j* enters the focal market, but also require expectations about the probabilities that all rivals enter all other markets (for the sake of calculating MMC). Given that calculating the measure of MMC in equation (1) requires about seven hours *for a given pattern of expected entry* (using a FORTRAN program), I cannot use a method that requires repeated calculation of MMC.

How the expectations in (2) are modeled depends on what assumptions we are willing to make. As a starting point, consider the case where the firm bases its expectations on where the rivals were last period and an updating term *v*:

$$E(MMC_{t,t}) = MMC_{t,t\text{-}1} + v_{imt} \quad (3)$$

The simplest form of these expectations is from the firm that adopts what in philosophy is called the Principle of the Uniformity of Nature (PUN; see Sober (1988)), which assumes that the present will be like the past. The PUNning firm has *v* in (3) = 0, and the econometrician is then free to use $MMC_{t,t\text{-}1}$ as a proper regressor. However, to use $MMC_{t,t\text{-}1}$ as a regressor in place of $E(MMC_{t,t})$ does *not* require the econometrician to adopt the assumption that the firm is a PUNner. Putting equation (3) into equation (2), we have:

$$Y_{imt} = \ldots + \beta_1 MMC_{t,t\text{-}1} + (\beta_1 v_{imt} + \varepsilon_{imt}) \quad (4)$$

As long as *v* is uncorrelated with $MMC_{t,t\text{-}1}$ and the other regressors, and $MMC_{t,t\text{-}1}$ is a predetermined regressor,[26] then the new composite error term in the parentheses in (4) satisfies the usual requirements for OLS estimates to be unbiased and consistent. For *v* to be uncorrelated with $MMC_{t,t\text{-}1}$, however, requires that the firm believe that the change in MMC is a "memoryless" process, in that it is uncorrelated with the level of MMC last period.

A more general formulation of expectations is:

$$E(MMC_{t,t}) = MMC_{t,t} + \eta_{imt} \quad (5)$$

Here the expectation is decomposed into the actual value of MMC at time *t* and the forecast error η. If we can assume that η is idiosyncratic forecasting error—as it would be, for example, if the firm held rational expectations and all factors observed by the firm are included in the regression—then η can be grouped with the other error term, as in (4), without creating any difficulty. However, $MMC_{t,t}$ is likely to be endogenous through its correlation with ε. The same factors in ε affecting firm *i*'s entry decision that are known to the firms but unknown to the econometrician may influence the entry decision of rivals, which in turn affects $MMC_{t,t}$. Thus, while there are conceivable assumptions about expectations under which $MMC_{t,t\text{-}1}$ is a valid regressor, it appear to be unlikely that $MMC_{t,t}$ ever would be. This distinction appears to be lost in some of the literature (e.g., Alcantara and Mitsuhashi, 2011)

However, valid estimation under assumption (5) is possible if a valid instrument for $MMC_{t,t}$ is available. I argue that $MMC_{t,t\text{-}1}$ suits the requirements. It is highly correlated with $MMC_{t,t}$ ($r = 0.70$), and after $MMC_{t,t}$ is included in equation (2), $MMC_{t,t\text{-}1}$ is plausibly exogenous. Thus, while $MMC_{t,t\text{-}1}$ is a valid regressor only under restrictive assumptions, it use as an instrument appears to be on much stronger

[26] A *predetermined* regressor is one uncorrelated with current and future error terms.

footing. All the discussion regarding expectations for $MMC_{t,t}$ also applies to NR_{imt}. Therefore similar considerations are involved with using NR_{imt-1} as a regressor and as an instrument.

B. Results

We begin the empirical examination with a few summary statistics, to get a feel for these markets. Of the 42,962 opportunities for entry in the dataset, the firm entered (or stayed in the market) 88% of the time. The number of rivals to the focal firm in the market averages 6.6. On average the focal firm meets one other firm offering ADSL in each market, a firm offering cable modem service in three out of four markets, 1.75 satellite broadband firms per market, one firm offering fixed wireless broadband out of every three markets, and two mobile wireless firms in every three markets.[27] There is significant MMC present. $MMC_{t,t}$ averages 0.166 across as markets, periods, and potential entrants. Recall that this figure means that when the focal firm considers entering a market, on average it will meet its rivals there in 16.6% of its markets nationwide. The distribution of $MMC_{t,t}$ is in Figure 1. In about 23% of markets, $MMC_{t,t}$ is zero. In such markets, the focal firm either faces no rivals at all, or the rivals it does (or would) face it does not meet elsewhere. This is about five times more likely to happen in rural areas than urban areas, where there are fewer CLECs and cable modem firms, and any competitors are more likely to be satellite firms, which do not count toward MMC. Summary statistics for the rest of the data are in Table 2.

1. Simple expectations

I begin with estimations based on equation (3) for the expectations for MMC and the presence of rivals in the market. Under the assumptions that v in equation (3) is uncorrelated with the other regressors, and that *MMC* and *NR* are predetermined regressors, the coefficients from OLS regression are consistent and the coefficient on $MMC_{t,t-1}$ is the impact of expected $MMC_{t,t}$. Table 3 contains the results of two OLS regressions. Regression 1 in Table 3 illustrates the potential pitfall of omitted variable bias that can plague empirical investigations of MMC. When $MMC_{t,t-1}$ is the only regressor included, its coefficient is large and highly significant. If the estimated coefficient, 0.475, were a causal impact it would imply that the focal firm is 47.5 percentage points more likely to enter a market in which it meets all its multimarket rivals in all the other markets it is entering the same period, compared to a market in which it meets no multimarket rivals. However, this estimate suffers from severe omitted variable bias. Attractive markets will naturally contain many multimarket rivals even in the absence of strategic considerations. Once market and focal firm related control variables are included as regressors, in Regression 2, the coefficient falls to 0.187. While still highly significant and relatively large, comparing the two estimates shows that more than half of the apparent impact of MMC from Regression 1 was due to the correlation of $MMC_{t,t-1}$ with other factors that drive the entry decision.

The firm related variables included in Regression 2 are an indicator for the presence of the firm in the focal market last period (*firm presence*$_{t-1}$),[28] the number of broadband rivals in the market (NR_{imt-1}, listed

[27] The latter figure includes some double counting, because I haven't yet removed the focal firm from this count and some ILECs also offer mobile broadband.

[28] To be precise, the indicator variable takes value 1 only if the firm offered ADSL in the focal market at *t*-1. Even if the firm offered broadband of some other type, the regressor is 0. If one splits the indicator variable into two (one for offering

as *# rivals*$_{t-1}$ in the table), and the log distance to the nearest other market in which the firm enters at *t* (*nearest*$_t$). The variable *firm presence*$_{t-1}$ is not always equal to y_{t-1}, because the former is adjusted to account for mergers and other forms of corporate reorganization.[29] *Firm presence*$_{t-1}$ controls for the presence of sunk costs involved with de novo entry in a market. When there are sunk costs of entry, once a firm has entered it is less costly to continue to offer service in subsequent periods. Thus, one would expect the coefficient on *firm presence*$_{t-1}$ to be positive, which it is (0.606). The high degree of economic and statistical significance of this estimate suggests that sunk costs play an important role in entry decision into broadband, a result in accord with Xiao and Orazem (2011). Without market fixed effects in the specification, however, *firm presence*$_{t-1}$ may also be picking up the impact of unobserved market specific factors relevant for entry.

The sign of the coefficient on *# rivals*$_{t-1}$ is equivocal a priori. Under full information among firms, reasonable assumptions about the nature of post-entry competition, and a complete set of all confounding factors for the entry decision, a larger number of firms in a market should lead to a negative coefficient, for entry would be less profitable. However, when information is incomplete or when the number of rivals proxies in part for market-specific factors inadequately controlled for in the regression, the sign of the coefficient for *# rivals*$_{t-1}$ may be positive. For example, when firms receive independent private signals about the profitability of a market, a larger number of competitors may signal to the focal firm that entry is more desirable than otherwise would be expected. Since the present purpose of including this variable in the regression is to control for omitted variable bias that may affect the apparent impact of MMC, I do not pursue which story is correct here (and indeed, the sign of this coefficient switches around between specifications).

The purpose of including *nearest*$_t$ is twofold. First, given the nature of broadband network infrastructure, is it typically less costly to deploy broadband service in an area close to where broadband is deployed elsewhere. This is for two reasons. It may be that a neighboring market is in the same wire center serving area, and broadband equipment deployed in the central office can be used to serve customers in both markets. Even when that is not the case (and given that I tried not to make markets too small, if may often not be the case), there may be other economies of agglomeration of network traffic in the network at levels beyond the central office. The second purpose that *nearest*$_t$ serves is to proxy for unobserved spatial correlation in cost or demand. A local cost or demand shock may affect several neighboring markets, and thus controlling for entry in nearby areas through *nearest*$_t$ helps to control for such shocks.

The market specific variables included in Regression 2 include several measures of the market size: the log number of households and establishments, as well as the population growth rate. Demographic characteristics of the area include the median age in quadratic form and educational attainment. Socioeconomic factors include log median household income and the unemployment rate specific to the

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broadband of the focal type at *t-1*, another for offering broadband of another type at *t*-1), the coefficient on MMC changes little.

[29] Consider, as one of the many examples I adjusted for, the case of a merger between focal firm A and another firm B in period *t*. When A was not present last period but B was, *firm presence*$_{t-1}$ = 1 because no sunk costs needed to be paid for A to enter the market.

market. Four cost-related factors are included: population density, the fractions of the land area covered by snow or ice and wetlands, and the standard deviation of the elevation of the land area.[30] Most of the estimated coefficients for these control variables have the expected signs—for example, the firm is more likely to enter larger markets—but since these variables are not of primary interest for present purposes, I do not discuss them further.[31] Although all the control variables in Regression 2 are included in all subsequent regressions, they are not shown in subsequent tables.

In Regression 3, also reported in Table 3, the specification of Regression 2 is repeated with the addition of market-specific fixed effects.[32] The fixed effects capture the impact of all time-constant factors in the market—i.e., market-specific entry shocks—observed and unobserved. Including the fixed effects halves the apparent impact of MMC from Regression 2. The new coefficient on $MMC_{t,t\text{-}1}$ is 0.093 and is still highly statistically significant. The significance level on the other control variables generally falls, as is typical in such panel data estimations, since there is not as much variation over time in these variables within a market as there is between markets. Observed regressors that do not vary over time (landcover and elevation variables) are absorbed into the fixed effects.

Before leaving this section, I note that there is a potential endogeneity problem regarding the regressor *firm presence*$_{t\text{-}1}$ in Regression 3. It is well known that simple fixed effects regression in dynamic panel data models leads to inconsistent estimates (Hsiao, 1986). While the specification adopted in Regressions 2 and 3 is not a simple dynamic one-- *firm presence*$_{t\text{-}1}$ is not identical to $y_{t\text{-}1}$—the same endogeneity problem may arise. In future work I intend to explore this further.[33] For now, the hope is that if there is an endogeneity problem, it mainly afflicts the estimated coefficient on *firm presence*$_{t\text{-}1}$, not the impact of MMC. However, given the potential problems with including market level fixed effects, I do not use the method further in this preliminary version of the paper.

Summarizing the results of this section, we have found that MMC apparently matters a lot for the entry decision of ILECs into the ADSL broadband market. Regressions 2 and 3 suggest that the impact of a one unit increase in $MMC_{t,t}$–a change from no multimarket contact to complete multimarket contact—on entry is in the range of nine to 19 percentage points.

2. A deeper inquiry into MMC: SOI and TOP

In this section, I take a closer look at why MMC affects the entry decision of broadband firms. The first hypothesis to explore is SOI created by heterogeneity among firms within a market. Bernheim and Whinston (1990) show that differences in cost among firms can give MMC a role in sustaining tacitly collusive agreements. This suggests looking for evidence that cost factors specific to the focal firm and the market affects the degree of influence that MMC has on entry. Under the SOI hypothesis, a variable

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[30] The elevation variable is meant to capture the presumed increased cost of deploying telecommunications infrastructure in mountainous areas.

[31] The most puzzling finding is that wealthier areas are associated with a *lower* probability of entry. However, the marginal effect is small: a 1% increase in median income is associated with only a 0.03 percentage point decrease in the likelihood of entry.

[32] If a random effects specification is chosen instead (results not shown), the coefficient and significance of the coefficient for MMC is nearly identical to that from Regression 2. Given how different the fixed effects estimates are, it is likely that a Hausman test would reject the RE model (to be done…).

[33] Some form of Arellano-Bond or Blundell-Bond estimation can be adapted.

that pertains to a firm having lower relative cost in a market will increase the magnitude of the impact of $MMC_{t,t\text{-}1}$ on entry. As noted above, the regressor $nearest_t$ should be negatively correlated with cost. To convert it to a relative measure ($relative\ distance_{t,t\text{-}1}$), I divide $nearest_t$ by the average value of the same measure last period for potential entrants the market.[34] Furthermore, since the SOI hypothesis concerns keeping rivals out of "home" markets (i.e., where the focal firm has low relative cost), the impact of MMC on entry should be less where competitors have already entered the market (Baum and Korn, 1996). Thus in Regression 4, reported in Table 4, $relative\ distance_{t,t\text{-}1}$ and $\#\ rivals_{t\text{-}1}$ are interacted with $MMC_{t,t\text{-}1}$, and the coefficients on the interaction terms are the estimates of interest. The estimated coefficient on the interaction of $MMC_{t,t\text{-}1}$ and $relative\ distance_{t,t\text{-}1}$ is negative and highly significant, in accord with SOI. The same is true for the interaction of $MMC_{t,t\text{-}1}$ and $\#\ rivals_{t\text{-}1}$. Thus, how the impact of MMC varies across markets is in the manner exactly predicted by the SOI hypothesis.

In Regression 5, I turn to the TOP hypothesis. Under the TOP hypothesis, MMC causes price-cost margins to fall in markets where the collusion condition is met with slack, as the slack is transferred to other markets where the condition does not bind. In latter markets, margins rise. Therefore, the impact of MMC on entry should be lowest in markets where the slackness of the collusion constraint is greatest. Variables that affect the slackness of the collusion constraint, whether in the aggregate or in the local market, include the following: 1) the number of other markets in which the focal firm expects to meet its multimarket rivals from the focal market (averaged over multimarket rivals in *m*; denoted $\#\ MMC\ contacts_{t,t\text{-}1}$); 2) the fraction of rivals' total lines in the state that are business lines; 3) the fraction of rivals' total lines in the state that are relatively fast residential lines;[35] and 4) an index of the speed of rivals' total lines in the state. The first variable relates to the aggregate slackness in the incentive constraint. As Sorenson (2007) suggests, "the more contacts firms have, the greater are their chances of finding slack in their incentive constraints that can be used to shore up collusion where it is not otherwise sustainable" (124-5) . The other variables are directly associated with the expected level of competition in the market. The business niche of the telecommunications market is generally more competitive than the residential side (variable 2). When competitors offer higher speeds to their customers, they may be expected to be fiercer rivals as well (variables 3 and 4).[36] According to the TOP hypothesis, the sign of the interaction of each of these variables with $MMC_{t,t\text{-}1}$ should be positive.

In order to isolate the impact of *# MMC contacts* on entry, it is important to control for the overall scale of the firm. A larger firm operating in more areas will naturally have higher values of *# MMC contacts*. To control for the scale of the firm each period, and indeed to control for all firm-period specific unobserved factors, I switch from OLS to panel data fixed effects regression, where the fixed effect is specific to the firm and period. The fixed effects also control for other firm-period factors included by

[34] I only have location data for CLECs and a subset of cable modem firms. Any potential entrant among these is included in the denominator of $Relative\ distance_{t,t\text{-}1}$.

[35] For this variable, "relatively fast" means speed in excess of 200 kbps in *both* directions, instead of merely in the fastest direction. This is still relatively slow by current standards, but there are no other measures of speed specifically for residential lines in Form 477 during these years. About 68% of focal and 74% of rival firms' residential lines are "fast" by this definition.

[36] Due to the nature of the data available, the line counts are at the state level and do not pertain to the market. They thus proxy the overall threat posed by the rival, not a market specific threat to the focal firm. Nevertheless, variables 2-4 vary across markets in a period because the identities and number of rivals varies.

other authors in the literature on MMC (e.g., the geographic dispersion of the firm, as in Haveman and Nonnemaker (2000)).

The results for Regression 5, in the middle column of Table 4, provide only scant evidence for TOP. The coefficient on *# MMC contacts*$_{t,t\text{-}1}$ × *MMC*$_{t,t\text{-}1}$ is positive and significant.[37] However, the coefficients on the other three interaction terms are either of the wrong sign (variables 2 and 3) or insignificant (variable 4). The unexpected negative coefficients on two of the competition variables may actually provide evidence for SOI. Just as the impact of MMC on facilitating SOI should be negatively related to the number of rivals, it may also be negatively related to the expected threat posed by those rivals.

Regression 6 combines the TOP and SOI variables in the same estimation. The same fixed effects specification is used as in Regression 5. One small change was made to the specification of the SOI variables: the square of *relative distance* was included, since significant nonlinearity was found here. The same general conclusions from the separate estimations still hold: the SOI-specific interactions are significant and consistent with the SOI hypothesis,[38] while the TOP-specific interactions are not, excepting the interaction of *# MMC contacts*$_{t,t\text{-}1}$ with *MMC*$_{t,t\text{-}1}$ as before. On balance, it appears that MMC matters in these markets less through the shifting around of slackness in the collusion constraint than through the sustenance of SOI.

3. Great expectations: IV estimations

In this final empirical section I re-estimate the models based on equation (5) for the expectations for MMC and the other variables not yet observed at the time the entry decision is made. Under the assumptions that η in equation (5) is uncorrelated with the other regressors, and that *MMC* and *NR* are predetermined regressors, the coefficients from IV regression using *MMC*$_{t,t\text{-}1}$ to instrument for *MMC*$_{t,t}$ (and similarly for the other variables) are consistent. While the assumptions on the expectation-forming process are more realistic, the switch from OLS to IV entails inevitable loss of precision in the estimates.

Regression 7 is like Regression 2, except that *MMC*$_{t,t}$ and *# rivals*$_{t,t}$ replace *MMC*$_{t,t\text{-}1}$ and *# rivals*$_{t,t\text{-}1}$ in the regression equation and the latter pair are used instead as instruments. The strength of the instruments is high. In the first stage regressions, the F statistics for the excluded instruments are 2063 for *MMC*$_{t,t}$ and 10314 for *# rivals*$_{t,t}$, indicating that the instruments are strong, while Shea's partial R squared measures (Shea, 1997) are 0.40 and 0.35, respectively.[39] In the second stage regression, the coefficient on *MMC*$_{t,t}$ is estimated to be 0.29, somewhat different than the coefficient on *MMC*$_{t,t\text{-}1}$ in Regression 2(as is to be expected with IV estimation) but highly significant.

Regression 8 in Table 5 repeats Regression 7 but with a different instrument for *MMC*$_{t,t}$. If there are market-period shocks that create endogeneity problems in the entry equation that are correlated with similar shocks to nearby markets, then the spatial dependence among markets may render *MMC*$_{t,t\text{-}1}$ an invalid instrument. To see this, denote the market-period shock u_{mt}. The shock creates an (additional)

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[37] While this result is consistent with TOP, it is not necessarily inconsistent with SOI—it is just less clear "why the frequency of contact would be essential to an SOI arrangement" (Sorenson, 2007, p.124).
[38] This is despite the fact that Regression 6 includes firm-period fixed effects, which Regression 4 did not.
[39] Furthermore, none of the host of joint tests for weak instruments and underidentification performed by the Stata add-on module `ivreg2` with the `first` option come close to indicating any problem with the strength of the instruments.

endogeneity problem for $MMC_{t,t}$ if u_{mt} is correlated with $MMC_{t,t}$ and also directly affects the entry decision. In that case, u_{mt} is one more term grouped with the error term in equation (2) . Assume first that the market-period shock u_{mt} satisfies $E(u_{mt}\, u_{nt}) = 0$ for any $n \neq m$. Then note that the reason $MMC_{t,t\text{-}1}$ makes a good instrument for $MMC_{t,t}$ is that shock u_{mt} is uncorrelated with the focal firm's presence in other markets at *t* (since the shocks are not related across markets)[40] and is also uncorrelated with the market presence of the rivals in the previous period (since that is predetermined). However, if $E(u_{mt}\, u_{nt}) \neq 0$ for markets *n* that are near to market *m*, then the shock in *m* may influence the entry decision in nearby markets and therefore $MMC_{t,t\text{-}1}$. My solution is to construct a new measure of $MMC_{t,t\text{-}1}$, denoted $MMC^{50+}_{t,t\text{-}1}$, that excludes all other markets with 50 miles of the centroid of market *m*. This instrument is also strong, but (naturally) not as strong as $MMC_{t,t\text{-}1}$.[41] With this instrument, the coefficient on $MMC_{t,t}$ remains positive and is still highly significant.

In Regression 9, I repeat estimation 6 using instruments as in Regression 7. The variables *relative distance* and *# MMC contacts* are also treated like the MMC measure: the (*t,t*) versions are used in the regression equation, are treated as endogenous, and are instrumented with their (*t,t*-1) versions. None of the conclusions about the sign or significance of the variables testing the TOP and SOI hypotheses changes in Regression 9, compared to Regression 6, with one exception. The coefficient on $MMC_{t,t}\times\#\ rivals_{t,t}$ is not significant at the 5% level, but barely so: the *p* value is 0.053.

V. Discussion and Conclusions

The work here uncovers evidence that consideration of MMC is part of the entry decision in broadband markets. Unlike much of the previous literature, I test to see whether the conclusions survive correction for endogeneity of the key measure of MMC. They do. Furthermore, exploration of theories about why MMC matters points toward the Spheres of Influence phenomenon; evidence for the Transfer of Power phenomenon is either contradictory or weak. By uncovering evidence that MMC plays a role in entry decisions in the broadband market, the results argue for a careful consideration of external market factors when undertaking merger review or other antitrust exercises.

There are many aspects in which the current work can be improved. As discussed in the text, econometric models suited to dynamic panel data with fixed effects must be explored. One can always look for better instruments, as well. One avenue may be to exploit the information about mergers and how they affect the competitors in the local markets, as suggested (in spirit, but not detail) by the work of Waldfogel and Wulf (2006). Finally, instead of only included ILECs in the estimation, I am gathering

[40] But is shock u_{mt} not correlated with $MMC_{t,t\text{-}1}$ through the focal firm's presence in the focal market? No. By definition of all the measures of MMC, for purposes of the calculations the focal firm is always treated as present in the focal market, regardless of the actual entry decision.

[41] In the first stage regression for $MMC_{t,t}$, the F statistic for the excluded instruments drops to 548, which is well above the rule-of-10 threshold. Similarly, none of the joint tests for weak instruments and underidentification (see footnote 39) indicate that the instrument is weak. However, the Shea's partial R squared measure falls to 0.092, yielding some concern that the instrument is much less strong than $MMC_{t,t\text{-}1}$ is. There is no known critical value for Shea's measure that indicates an instrument is weak. The lower Shea's R squared may nevertheless explain why the estimated coefficient in Regression 8 is so different than the estimates in Regressions 2 and 7.

information to allow the inclusion of cable modem providers and CLECs as well. Adding these other types of firms will allow exploration of additional hypotheses that involve heterogeneity among firms.

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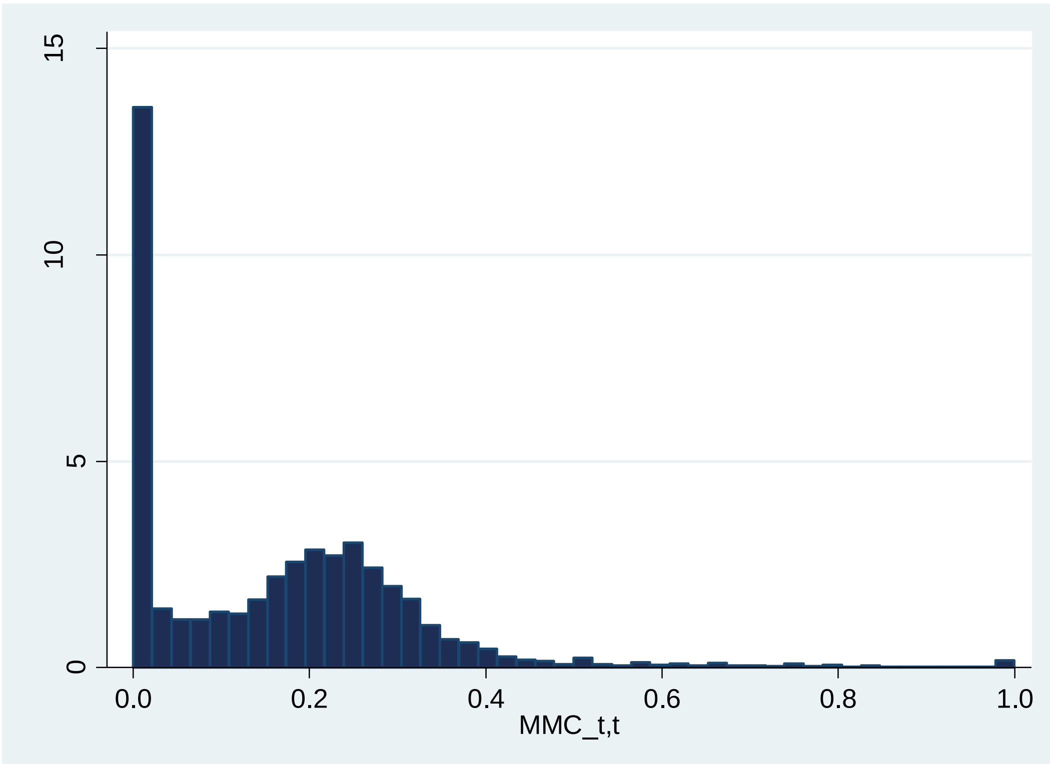
Figures

Figure 1: The Distribution of $MMC_{t,t}$



Tables

Table 1: Vintage of the Data and Grouping into Periods

Period	Forms 477 Included	Year of matched external economic and demographic data
0	June 30, 2005	2005
1	December 31, 2005 June 30, 2006	2006
2	December 31, 2006 June 30, 2007	2007
3	December 31, 2007 June 30, 2008	2008

Table 2: Summary Statistics for the Data

Variable	Obs	Mean	Std. Dev.	Min	Max
Y_{imt} (Firm presence in market)	42,962	0.878	0.327	0.000	1.000
Multimarket contact: $MMC_{t,t}$	42,962	0.166	0.159	0.000	1.000
firm presence$_{t-1}$	42,962	0.832	0.374	0.000	1.000
# rivals$_t$	42,962	6.589	3.644	0.000	27.00
dist. to nearest other presence, log	42,947	1.963	0.963	-0.676	8.424
relative distance$_{t,t}$, log	42,947	-4.002	1.640	-7.669	5.274
# multimarket contacts per rival$_{t,t}$, log	42,962	6.047	3.621	0.000	9.030
competitor business lines	42,962	0.436	0.302	0.000	1.000
competitor fast residential lines	42,962	0.740	0.349	0.000	1.000
competitor speed index	42,962	0.173	0.128	0.000	0.608
# households, log	42,962	7.501	1.549	0.000	12.01
# establishments, log	42,962	4.549	1.773	-0.693	9.623
median HH income, log	42,962	10.55	0.320	8.889	12.14
pop growth rate, annualized	42,962	0.008	0.028	-0.266	0.187
median age	42,962	43.75	4.589	21.60	79.50
education: high school diploma	42,962	0.343	0.092	0.043	0.636
education: some college, no 4 yr deg.	42,962	0.269	0.065	0.000	0.646
education: 4 year degree or more	42,962	0.183	0.121	0.000	0.801
unemployment rate, %	42,962	4.375	2.595	0.000	50.00
population density (pop/SqMi), log	42,962	4.425	2.241	-2.303	11.58
snow, ice landcover, %	42,962	0.000	0.002	0.000	0.148
wetlands landcover, %	42,962	0.058	0.100	0.000	0.909
elevation (s.d.)	42,962	45.75	74.91	0.040	858.7

Table 3: Estimations Exploring the Impact of MMC on Entry

Y_{imt} = 1 if firm is present in market	**Regression 1 (OLS)**	**Regression 2 (OLS)**	**Regression 3 (Market FE)**
$MMC_{t,t-1}$	0.4753	0.1871	0.0925
	(0.0138)**	(0.0089)**	(0.0107)**
firm $presence_{t-1}$		0.6059	0.1511
		(0.0063)**	(0.0064)**
# $rivals_{t-1}$		-0.0008	0.0072
		(0.0003)*	(0.0005)**
dist. to nearest other presence, log		-0.0784	-0.1282
		(0.0023)**	(0.0055)**
# households, log		0.0327	0.7704
		(0.0029)**	(0.2503)**
# establishments, log		0.0088	-0.0336
		(0.0023)**	(0.0144)*
median HH income, log		-0.0303	-0.0679
		(0.0053)**	(0.0972)
pop growth rate, annualized		0.0969	-2.4751
		(0.0431)*	(1.3290)
median age		-0.0107	-0.0276
		(0.0024)**	(0.0141)
median age squared		0.0001	0.0003
		(0.0000)**	(0.0002)*
education: high school diploma		0.1136	-0.7410
		(0.0223)**	(0.7830)
education: some college, no 4 yr deg.		-0.0367	-2.5538
		(0.0193)	(0.7421)**
education: 4 yr degree or more		0.0484	-1.5859
		(0.0173)**	(0.8510)
unemployment rate, %		-0.0048	-0.0452
		(0.0006)**	(0.0036)**
pop/SqMi, log		-0.0391	-0.3085
		(0.0014)**	(0.1840)
snow, ice landcover, %		1.3348	
		(0.4269)**	
wetlands landcover, %		0.0167	
		(0.0104)	
elevation (s.d.)		-0.0002	
		(0.0000)**	
constant	0.8036	0.9483	-0.5742
	(0.0040)**	(0.0687)**	(2.1850)
F statistic	1,185.73	1,289.23	110.94
R^2	0.054	0.649	0.145
Adjusted R^2 (OLS) or Within R^2 (FE)	0.054	0.648	0.200

* p<0.05; ** p<0.01

Notes: N = 42,962. S.e.'s are robust to heteroskedasticity and account for clustering within markets.

Table 4: Estimations Exploring SOI vs. TOP

Y_{imt} = 1 if firm is present in market	**Regression 4 (OLS)**	**Regression 5 (Firm-Period FE)**	**Regression 6 (Firm-Period FE)**
$MMC_{t,t-1}$	0.1254	0.0620	0.0425
	(0.0183)**	(0.0324)	(0.0397)
$MMC_{t,t-1}$×(relative $distance_{t,t-1}$, log)	-0.0284		-0.0384
	(0.0029)**		(0.0143)**
$MMC_{t,t-1}$×(relative $distance_{t,t-1}$, log)^2			-0.0081
			(0.0020)**
$MMC_{t,t-1}$×(# $rivals_{t-1}$)	-0.0130		-0.0091
	(0.0028)**		(0.0033)**
firm $presence_{t-1}$	0.6071	0.6827	0.6817
	(0.0063)**	(0.0030)**	(0.0030)**
# $rivals_{t-1}$	0.0014	-0.0026	-0.0006
	(0.0006)*	(0.0005)**	(0.0008)
dist. to nearest other presence, log	-0.0770	-0.0706	-0.0739
	(0.0023)**	(0.0020)**	(0.0020)**
$MMC_{t,t-1}$×(# MM contacts per $rival_{t,t-1}$)		0.0116	0.0149
		(0.0031)**	(0.0032)**
$MMC_{t,t-1}$×(competitor business lines)		-0.0727	-0.0495
		(0.0307)*	(0.0309)
$MMC_{t,t-1}$×(competitor fast residential lines)		-0.1639	-0.1416
		(0.0268)**	(0.0274)**
$MMC_{t,t-1}$×(competitor speed index)		0.1201	0.1458
		(0.0909)	(0.0910)
# MM contact $markets_{t,t-1}$		0.0025	0.0019
		(0.0004)**	(0.0005)**
competitor business lines, proportion		-0.0000	-0.0025
		(0.0062)	(0.0062)
competitor fast residential lines, proportion		0.0176	0.0140
		(0.0053)**	(0.0054)**
competitor speed index		0.0103	0.0044
		(0.0196)	(0.0196)
constant	0.9349	0.5382	0.5599
	(0.0686)**	(0.0554)**	(0.0555)**
Controls as in Estimation 2	included	included	included
F statistic	1,173.63	3,553.87	3,192.03
R^2	0.649	0.634	0.633
Adjusted R^2 (OLS) or Within R^2 (FE)	0.649	0.679	0.680

* $p<0.05$; ** $p<0.01$

Notes: N = 42,947. In Regression 4 only, s.e.'s are robust to heteroskedasticity and account for clustering within markets. (Regressions 5 and 6: this is yet to be done).

Table 5: Instrumental Variables Regressions

Y_{imt} = 1 if firm is present in market	Endogenous?	Regression 7 (IV)	Regression 8 (IV)	Regression 9 (Firm-Period FE + IV)
$MMC_{t,t}$	Yes	0.2932	0.5653	0.1292
		(0.0158)**	(0.0393)**	(0.0729)
# $rivals_t$	Yes	0.0028	0.0020	-0.0005
		(0.0008)**	(0.0008)*	(0.0015)
$MMC_{t,t}$×(relative $distance_{t,t}$, log)	Yes			-0.1084
				(0.0354)**
$MMC_{t,t}$×(relative $distance_{t,t}$, log)^2	Yes			-0.0480
				(0.0100)**
$MMC_{t,t}$×(# $rivals_{t-1}$)	Yes			-0.0130
				(0.0067)
$MMC_{t,t}$×(# MM contacts per $rival_{t,t}$, log)	Yes			0.0208
				(0.0053)**
$MMC_{t,t}$×(competitor business lines)	Yes			-0.0865
				(0.0553)
$MMC_{t,t}$×(competitor fast residential lines)	Yes			-0.2407
				(0.0491)**
$MMC_{t,t}$×(competitor speed index)	Yes			0.2389
				(0.1502)
firm $presence_{t-1}$		0.5971	0.5883	0.6751
		(0.0064)**	(0.0067)**	(0.0031)**
dist. to nearest other presence, log		-0.0778	-0.0741	-0.0783
		(0.0024)**	(0.0025)**	(0.0025)**
# MM contacts per $rival_{t,t}$	Yes			0.0043
				(0.0010)**
competitor business lines, proportion				0.0001
				(0.0078)
competitor fast residential lines, proportion				0.0237
				(0.0074)**
competitor speed index				-0.0404
				(0.0274)
constant		1.0053	1.1270	0.6980
		(0.0716)**	(0.0778)**	(0.0630)**
Controls as in Estimation 2		included	included	included
Instrument for $MMC_{t,t}$		$MMC_{t,t-1}$	$MMC^{50+}_{t,t-1}$	$MMC_{t,t-1}$
χ^2 statistic		22,614.07	21,962.84	1,252,892
R^2		0.632	0.594	0.628
Adjusted R^2		0.632	0.594	NA

* p<0.05; ** p<0.01

Notes: N = 42,947.