Learning Costs and Peer Effects in Mobile Phone Service Provision

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Abstract

I estimate the extent of learning costs and peer and advertising effects in the market for postpaid wireless service. Switching costs and peer effects could create market power in the wireless market, which is perennially of interest in an industry which is dominated by a small number of firms, often searching for merger opportunities. Using an individual-level panel of 4.8 million consumers across two years, I find a large effect for learning costs, where consumers are only half as likely to choose a wireless service provider with which they have no prior experience. For peer and advertising effects, I consider the unique position of consumers who have moved between markets. Consumers who moved between markets are more likely to choose a provider with a larger market share in their home market. Both effects are robust to controls for consumer purchase history, individual-level demographic factors, and interaction effects with migration status. The results are consistent with consumers facing large switching costs due to learning, and forming long-lasting impressions of the quality of service providers from peers or advertising.

Introduction

The competitiveness of the telecommunications industry has been a source of intense regulatory interest since at least the breakup of AT&T in 1986, and continues today in evaluating the recent bid for a merger between T-Mobile Wireless and Sprint Wireless. Notably, the market for wireless cell phone service is dominated by four large providers, with few meaningful challengers. The extent of the market power held by these firms is important for evaluating the effects of dissolution and consolidation in the industry. Some potential sources of market power have been researched. This includes the effect of regulation (Faccio and Zingales, 2017), telephone number portability (Viard 2007; Maicas et al. 2009; Lee et al. 2006), and other country-specific factors in cross-country comparisons (Hausman and Ros, 2013). One important source of market power largely missing from empirical analysis of the wireless industry is consumer inertia, due to loyalty, switching costs, or peer effects. Consumer inertia has been researched in other industries that exhibit persistence in brand choices over time (Dube, Hitsch, and Rossi, 2010), but in general studies of wireless service provision lack the linked data over time needed to measure persistence at an individual level.

I am able to more directly measure some potential sources of market power by combining two features of a unique, individual-level panel. First, I observe a full set of consumer purchase histories. This allows me to control for switching costs and brand loyalty effects that keep consumers with their current provider. Being a consumer in the wireless market requires a phone, most of which are 'locked' to operate with only one provider. Additionally, some providers charge early termination fees for consumers who switch away before a certain number of months. Since I observe consumers' current provider at different points in time, I can control for these important direct switching costs and more generally for consumer brand loyalty. Also, through consumer histories, I observe the service providers with which consumers have previous experience. Since the quality of any service provider is uncertain, consumers might need to use a particular provider's service to know the level of network coverage, or the quality of customer service. Survey evidence has indicated consumers anticipate these 'learning costs' in the wireless market (Aydin et al. 2005). I find a very large effect of consumers' prior familiarity with a service provider. Consumers in my data are only half as likely to choose a provider with which they have no prior experience, consistent with facing high learning costs in the market for wireless service.

Second, I estimate how being in a market with a particular balance of market shares between carriers can have a long-term influence for consumers, even for providers with which they have no prior history. Previous research on the wireless service industry has indicated that peer effects play an important role in consumer descision-making, finding consumers are more likely to switch away from their current provider if their freinds do so (Han and Ferreira, 2014). However, identifying peer effects of this type using market shares are subject to a set of challenges raised by Angrist (2014) and earlier by Manski (1993), who note the potential sources of endogentiy in comparing individual-level outcomes to group level outcomes. In the spirit of Bronnenberg, Dubé, and Gentzkow (2012), who preformed a similar study in the packaged goods market, I address this endogeneity by leveraging a unique feature of North American telephone numbering system to take advantage of the variation between 'migrant' consumers who have moved between markets and 'non-migrant' consumers who have not moved between markets. Migrant consumers are unique because they have been exposed to two different sets of markets with two different sets of peers and advertising to form their impressions. So, I test if migrant consumers are more likely to choose service providers with larger market shares in their home markets. I find a small, but positive effect of home market shares on the likelihood of migrants to choose a particular provider in their current market, where migrants are between around 20%-40% more likely to choose a service provider with a 10 percentage point higher market share in their home market. When combined with the consumer purchase history information, this effect holds even for providers with which consumers have no prior history.

In the next section I describe the data, with a particular focus on how I am able to link consumer purchase histories, and determine a consumer's migration status. Next, I describe the model and assumptions required, and provide some evidence for the credibility of those assumptions. Last, I discuss the estimation procedure and results.

Data:

The data come from a telecom consultancy.[1] 4.8 million household-level observations are included in sample. Each observation includes information on household demographics, including age of head of household, ethnicity of head of household, annual household income, and household size. For each household in the data, the head of household is associated with a telephone number as of the beginning of 2015. Also observed for each telephone number is when the telephone number switched between wireless service providers anytime after the beginning of 2010, until the end of 2017. The switching history data are observed at the level of telephone number, so to be counted as a switch, the consumer would have to keep their phone number when switching to a new service provider. The ability for consumers to keep their wireless number is required by the Federal Communications Commission (FCC) under regulations enforced nationally starting in May of 2003. 'Prepaid' contracts, where payment is made in advance of using wireless service, often make keeping a phone number more difficult, and as a result prepaid consumers are more likely have to have gaps in their switching histories. The data include both consumers with service at both postpaid and prepaid brands, but I include only consumers of the top four postpaid brands in my analysis (Verizon Wireless, AT&T Wireless, T-Mobile Wireless, and Sprint Wireless). This also excludes consumers who have switched between prepaid brands and postpaid brands.

The demographic and switching history information is assembled from a set of proprietary data sources, including survey data, data from cellular network routing, and telephone number white page directories. Since proprietary considerations prevent full reporting on the provenance of the sample, and because inclusion in the sample is non-random, I present two comparisons to publicly available data. First, Table 1 presents a comparison of the sample demographic information to Census data. The sample very closely matches Census demographic profiles in median age, average household size, median annual household income

[1]Due to the proprietary nature of these data, identifying information here and elsewhere in the analysis is excluded by agreement

and the ethnicity of the head of household. The largest difference is in the proportion of head of households who report their ethnicity as white, where the sample has a slightly lower proportion (71%) compared to Census household data (79%). The age and income distributions are also very comparable, although the sample skews somewhat more middle-aged and somewhat more high-income. Overall, the demographic comparison is favorable to the potential external validity of the results, although some caution might be required in interpreting the results for very young, very old, or low-income consumers.

Table 1: Demographics in the Sample and Census

	Sample	Census
Median Age of Household Head	50.0	50.2[1]
Proportion under 25 years	0.008	0.039[2]
Proportion 25-44 years	0.334	0.331[2]
Proportion 45-65 years	0.484	0.396[2]
Proportion 65+ years	0.174	0.234[2]
Average Household Size	2.80	2.54[1]
Median Annual Household Income	$57,500	$56,516[1]
Proportion under $35,000	0.229	0.211[2]
Proportion $35,000 to $60,000	0.230	0.231[2]
Proportion $60,000 to $125,000	0.324	0.410[2]
Proportion above $125,000	0.217	0.148[2]
Proportion White Household Head	0.71	0.79[1]
Proportion Black Household Head	0.15	0.14[1]
Proportion Latino Household Head	0.12	0.13[1]

1: Census Tables HH1-HH8, 2: ACS 5-Year Estimates Table B19037

For a comparison of market shares in the sample to publicly reported market share data, Table 2 summarizes market shares by year using end of year (fourth quarter) shareholder reports. The shares are presented as a total of all subscribers of one of top four providers in a given year. Notably, market shares change very little from year to year. In general, quarterly reported information indicates postpaid consumers switch between providers at very low rates, usually less than 2% in any given month. The sample's market shares are very close to reported market shares, although consistently slightly below for Verizon Wireless and slightly above for T-Mobile Wireless. In the sample, T-Mobile's consumers are distributed more towards urban areas than Verizon, and it is possible the sample over-represents urban areas. However, it is also possible differences are due to how the shareholder numbers are reported.[2] However, the comparison still indicates the sample is a good representation of the competitive marketplace for wireless postpaid cell phone service.

In the data, a key source of variation is between wireless markets. The data include information about consumer's address at an individual level at the beginning of 2015, but does not include information on previous addresses. Differentiating migrant consumers and non-migrant consumers requires a determination of which consumers have moved. Wireless markets are defined here as a geographic area within which product characteristics for the same service provider are largely homogeneous. Migrants, for the purposes of this study, are people who move between cellular markets. A consumer who moves within a market is treated as a non-migrant, since the relevant product characteristics they face have not changed.

In the wireless service market, the main geographically differentiated product characteristic is network coverage. So, in defining cellular markets, I build off of geographic information

[2]Notably, T-Mobile reported lines added as part of it DIGITs service, in which customers could easily add many new phone numbers to their existing devices as added subscribers in the second quarter of 2017 (see, for instance the report in *FierceWireless* by Colin Gibbs in Jul 21, 2017, "T-Mobile's Digits accounted for 200K net adds-but not necessarily new customers-in Q2"). I am unaware of a consistent standard on how service providers count added lines per customer in their reported numbers. The firms generally do not report on their methods.

Table 2: Postpaid Phone Market Share by Year

	Sample	Reported
2014		
Verizon Wireless	0.39	0.42
AT&T Wireless	0.33	0.33
Sprint Wireless	0.12	0.12
T-Mobile	0.16	0.12
2015		
Verizon Wireless	0.40	0.42
AT&T Wireless	0.33	0.32
Sprint Wireless	0.11	0.12
T-Mobile	0.16	0.13
2016		
Verizon Wireless	0.40	0.41
AT&T Wireless	0.32	0.31
Sprint Wireless	0.11	0.12
T-Mobile	0.17	0.14

closely tied to physical network infrastructure. There exists a standard Type I/Type II error trade-off in defining too small or too large of an area, so I consider three candidate market definitions for robustness, and discuss the implications for classification error in each. The definition of cellular markets begins with how phone numbers are assigned. When a phone number is first activated, it is assigned to a "wire center" (also referred to as central office) which houses the physical network infrastructure which routes phone calls. Collections of these wire centers are called "rate centers", associated with a central point in V&H coordinate space.[3] The close association of rate centers with local physical network infrastructure helps ensure market conditions, network coverage, and other product characteristics consumers face are likely very similar near the same rate center.

Notably, there is no technological reason for tying cell phone numbers to any geographic area. Like other aspects of cellular infrastructure, rate centers are indicative of how much of the design of the cellular network system is actually built upon older land-line telephone systems. In the U.S., since the first introduction of mobile phones in the 1980's, mobile telephone numbers have used the same local numbers as land-line service, instead of having a 'mobile-only' digit or set of numbers, as in many places in Europe. For land-line telephones, calls made within a rate center were 'local' calls and calls made outside of the rate center were charged at a different rate, since it required using a different set of technology to connect the call over a longer distance. Numbers are apportioned to service providers by rate center in blocks of 10,000 numbers by the North American Numbering Plan Administration. So, when setting up a new land-line connection, a service provider draws upon its stock of numbers in the rate center in which the land-line connection is made. As mobile phone service grew out of existing systems for land-line phone service, mobile telephone numbering inherited several relevant features from land-line phone numbering, including the assignment of 10,000 number blocks to a local rate center.[4] Service providers do not report on exactly how they assign

[3]The V&H coordinate system was created in 1957 at AT&T to simplify the calculation of distance across the U.S. For ease of association with standard geographic sets, I converted these V&H coordinates into Latitude and Longitude.

[4]Consumers with 504 area code numbers experienced this first hand when Hurricane Katrina knocked out

wireless telephone numbers, but across the four major wireless service providers, service activation requires a credit check and a billing address, and the telephone number a consumer receives is based on the consumer's billing zip code. I attempted to sign up for service with all four of the major postpaid service providers to validate this.[5]

For two important reasons, rate centers are too granular a geography to use individually as market definitions. First, although rate centers provide good geographic information about which market characteristics a consumer faced at the time of service activation, it is much less clear how to associate a consumer's current address to a rate center. Since rate centers are defined as points in space, using them as markets would require associating a consumer's addresses based on distance and applying arbitrary cut-offs. Also, the differential stock of telephone numbers service providers have on different rate centers creates some geographic ambiguity, since two different providers could assign the same consumer a number from different local rate centers based on their stock of available numbers. This means rate centers in the same local area are best treated together, so differences in apportionment between them do not bias the results. In creating a collection of local rate centers to be considered together, there exists a standard trade-off. On the one side is incorrectly classifying a consumer as a migrant, when the product characteristics are the same in their home market where they activated service and their current market. On the other is incorrectly classifying a consumer as a non-migrant, when the product characteristics are different in their home market and their current market. To test the robustness of the results to market specification, three candidate geographic aggregations are tested.

The first candidate geographic definition leverages the most salient and familiar feature geographic information included in a telephone number, the Numbering Plan Area (NPA), or area code. A NPA consists of the first three digits of a phone number, and was introduced by the Bell corporation in the 1950's and 60's, as a way to allow for calling between longer

incoming call service to many wireless consumers, even those not living in New Orleans at the time.

[5]However, it is possible consumers could lie about their current zip code in order to get a preferred telephone number.

distances with "automatic" dialing (i.e. dialing without the need for a human operator). The definition and geographic boundaries of NPAs are handled by the North American Numbering Plan Administration, subject to regulations and directives from government organizations like FCC, but since 1997 in the U.S. run by a private company.[6] When new area codes are needed, either existing area codes are split into two different geographic areas, or a new area code is "overlaid" on an existing geographic area, so both codes apply to the same area. There are 227 unique NPAs in the sample (counting overlaid NPAs as the same), with an average of 21,391 observations in each. Since NPAs are based on a fixed set of numbers, the boundaries scale with population. For instance, four overlaid NPAs (212, 646, 917, and 332) are associated with Manhattan alone, whereas the 307 area code covers the entire state of Wyoming. The number of observations in a given NPA varies from 62 to 130,004, with a standard deviation of 16,800. This makes the NPA definition most susceptible to false positives. For instance, many consumers who currently live in a different borough of New York City might have a Manhattan area code, but be in the same relevant cellular market. 18.5% of observations are migrants under this definition.

The second candidate geographic definition is state. Notably, state has been the standard geographic definition in studies of brand preference leveraging differences in migration between markets.[7] Many larger states represent the opposite side of the classification trade-off compared to NPA. Urban areas within states for which all four service providers have good network coverage ought to be considered separately from rural areas within states where some competitors might have a network advantage. To return to the New York City example, industry bench-marking by RootMetrics gives all four major providers scores between 0-100 based on service quality metrics like upload/download speed and reliability in different markets. For New York City and the tri-state area in 2017, RootMetrics scored each of the top four postpaid wireless providers above 90 out of 100, but in the nearby Hudson Valley,

[6] FCC is required to hold a bidding process for this position. Neustar (formerly Lockheed Martin IMS) had won three bidding processes (1997, 2003, and 2012), but recently lost the contract to Ericsson in 2015.

[7] See, for instance Bronnenberg, Dubé, and Gentzkow (2012).

T-Mobile and Sprint both scored closer to 80.[8] So, state definitions might be more susceptible to false negatives than NPA definitions. However, like with NPAs, network coverage does not stop at state boundaries, and many cellular markets might also spill over state lines. This is particularly true of smaller states, like Rhode Island, but can apply around any state boundaries. There are an average of 95,211 observations per state, ranging from 3,648 to 523,527 with a standard deviation of 113,963. Only 5.65% of observations are migrants under this definition.

The preferred market definition is a cellular market area (CMA) as defined by the Federal Communications Commission (FCC, 1992). CMAs are combination of Metropolitan Statistical Areas (MSAs) as defined by the Office of Management and Budget (OMB), and FCC defined Rural Service Areas (RSAs). The inclusion of RSAs ensures full geographic coverage. There are 716 unique CMAs in the sample, 415 which are MSAs. There are an average of 6,782 observations in each CMA, ranging from 1,091 to 282,774 with a standard deviation of 20,462. The CMA definition is preferable, since it balances issues with using NPAs and states. For instance, the New York City CMA covers not just all the five boroughs, but also parts of New Jersey and Pennsylvania that likely have the same levels of network coverage and service quality. Yet, unlike the state definition, the Hudson Valley, where service provision is different, falls within its own CMA (Poughkeepsie-Newburgh-Middletown, NY). Somewhat more observations are migrants under the CMA definition than the NPA definition, at 25%. This implies the effect of having more granularity in rural areas through the inclusion of RSAs outweighs the effect of having less granularity in urban areas. For instance, the 307 area code covers all of Wyoming's six CMAs, including one for the second largest city, Casper, and two that overlap state boundaries: one for the Fort Collins, Colorado and Cheyenne, Wyoming border area and one that covers Yellowstone National Park in Wyoming and Idaho. Notably, the sample proportion of migrants compares very favorably with survey evidence that indicates that around 26% of people live more than an hour drive from family

[8] see Metro Area RootScore Reports: 2nd Half 2017, (2017).

members (Health and Retirement Study, 2015). Although CMAs are the preferred definition, all geographic specifications are presented and the main results are robust to changes in market definitions.

Model and Assumptions

Before discussing the model in detail, I provide an example to build an intuitive sense of the variation in the data being utilized. In the same market, migrants and non-migrants face the same set of product characteristics. If demand were driven by those characteristics, in a market without switching costs, we would expect migrant and non-migrant market shares to be similar. Table 3 presents the migrant and non-migrant market shares in a mid-sized midwestern metropolitan CMA (Market A) and a large southern metropolitan CMA (Market B). The market share for both Verizon Wireless and T-Mobile Wireless in the sample among migrants from Market B in Market A is more similar to non-migrants in Market B than it is to non-migrants in Market A. Similarly, market shares for Verizon Wireless and AT&T Wireless for migrants from Market A in Market B are more similar to non-migrants in Market A than to non-migrants in Market B.

Table 3: Postpaid Phone Market Share by CMA Migration

	Migrants from Market A in Market B	Non-Migrants in Market A
Verizon Wireless	0.16	0.11
AT&T Wireless	0.48	0.39
Sprint Wireless	0.14	0.14
T-Mobile	0.21	0.36
Observations	163	20,365

	Non-Migrants in Market B	Migrants from Market B in Market A
Verizon Wireless	0.55	0.47
AT&T Wireless	0.18	0.33
Sprint Wireless	0.13	0.07
T-Mobile	0.13	0.13
Observations	152,540	357

This variation, at a first pass, is suggestive of the conditions in migrants' home markets having some long-term effect on their decisions. Migrants are subject to the same set of product characteristics as non-migrants in their new market, but are also influenced by advertising and peer effects from their home market. Migrants form an impression of the quality of a particular provider in their home market, and this impression could persist, even when the objective set of product characteristics change with their new market. If this is the key distinction between migrants and non-migrants, then the differences in their behavior identify those long-lasting peer effects. However, these market share differences alone can have other causes. In particular, switching costs can drive a wedge between migrant and non-migrant outcomes. Consider the case of migrant and non-migrant consumers in Market A from Table 3. AT&T Wireless and T-Mobile Wireless have the two largest market shares in Market A among non-migrants. This likely represents an advantage from more attractive product characteristics in Market A. Many migrants to Market A, however, enter their new market with a different provider, representing the attractiveness of the product characteristics in their home market, where they first activated their wireless service. Even if those migrant consumers might want to switch to AT&T Wireless or T-Mobile Wireless based on superior product characteristics in Market A, high switching costs could prevent them.

Luckily, I observe consumer's current provider, so I can control for the rate at which migrants and non-migrants switch away from their current provider. This controls for first-order switching costs which consumers face, such as those from the cost of phones, or early termination fees. After controlling for current provider, I can estimate both a likelihood to switch to a new provider, and a likelihood to remain with a current provider. In Table 4, I present the share of consumers switching to Verizon Wireless, T-Mobile Wireless and Sprint Wireless for consumers who switched away from AT&T Wireless in Market A. Conditional on choosing to switch providers, migrants in Market A are still relatively more likely to switch to the provider with the higher market share in their home market (Verizon Wireless) than the provider with the smaller market share in their home market (T-Mobile Wireless). This is despite the other consumers in their current market choosing T-Mobile Wireless more than other providers. As before, it seems as if migrant consumers have some impressions about the relative quality of of these providers comporting as much to the situation in their home market as it does to the product characteristics they face in their current market.

Table 4: Postpaid Phone Share of Switches from AT&T Wireless by CMA Migration

	Non-Migrants in Market A	Migrants from Market B in Market A
Verizon Wireless	0.23	0.41
T-Mobile Wireless	0.54	0.35
Sprint Wireless	0.23	0.24
Observations	2,443	44

However, as before, attributing differences between migrants and non-migrants to those impressions would involve failing to fully account for switching costs. Switching wireless providers involves some amount of uncertainty as to the true quality of the service. Consumers might have to learn the quality of network coverage or customer service through trying the product. A larger portion of migrant consumers in Market A might have a prior history with Verizon Wireless, since after all, it is the market leader in their home market. If their prior history with Verizon Wireless lowered the learning cost associated with that provider, they would be more likely to choose it, all else equal. Luckily, I also observe consumers switching histories, so I can control for the rate at which consumers switch back to a provider with which they have prior experience. This variation also forms the basis of my estimates of learning costs discussed later.

Beyond differences due to switching costs, migrants and non-migrants might differ in individual-level characteristics. Table 5 presents a demographic comparison of migrants and non migrants at each geographic market level.

Table 5: Demographics by migration status

	NPA-level		State-level		CMA-level	
	Migrant	Non-Migrant	Migrant	Non-Migrant	Migrant	Non-Migrant
Average Age of Household Head	51.41	50.17	50.14	50.23	52.15	49.58
	(14.68)	(14.04)	(14.19)	(14.09)	(15.19)	(13.65)
Average Household Size	2.98	3.10	2.85	3.08	3.05	3.08
	(1.61)	(1.63)	(1.58)	(1.62)	(1.59)	(1.63)
Average Annual Household Income	$73,364	$68,355	$75,023	$69,912	$69,375	$70,477
	($49,455)	($47,910)	($49,143)	($48,528)	($48,320)	($48,559)
Proportion White Household Head	0.65	0.59	0.71	0.56	0.69	0.55
Proportion Black Household Head	0.11	0.15	0.10	0.16	0.12	0.15
Proportion Latino Household Head	0.09	0.13	0.08	0.13	0.10	0.14
Observations	897,886	3,683,524	247,351	4,581,410	1,219,809	3,635,952
Proportion of Sample	0.13	0.87	0.06	0.94	0.25	0.75

standard deviation in parentheses

Overall, migrant households and non-migrant households under both definitions had similar average age of the head of household and household sizes. Also, under all market definitions, a larger proportion of migrant head of households were white, and fewer were black or latino. Migrants had higher annual incomes, except for at the CMA market definition, where the two were very similar. The relative similarity between migrants and non-migrants on average in the CMA market definition is an additional reason to prefer it beyond what was discussed above. However, since the market definitions have some variation in the extent of migrant/non-migrant demographic differences, I return to the market definition comparison in evaluating the robustness of my results.

Crucially, I am able to control for these differences, which I observe, but unobserved individual-level differences between migrants and non-migrants which are clustered geographically by market is much more troublesome for identification. As an example, consider four markets inhabited by consumers geographically segregated by different rank ordering of their favorite color. Additionally, assume each favorite color causes an increased likelihood of choosing a particular wireless provider. A consumer in Market A, whose favorite color was red, and second favorite color was magenta lives in a market where Verizon Wireless and T-Mobile Wireless are the two dominant firms. If the consumer moved to a new market where Sprint Wireless and AT&T Wireless were the two dominant firms, because consumers in that market preferred the colors yellow and blue, then the migrant's choices would more closely align with their home market. The cause of these differences would be an individual difference in preferences which happened to vary across markets instead of peer effects from those markets. I discuss this concern at more length after presenting the model, but in general, I am unable to control for unobserved individual-level differences which both influence demand for postpaid wireless service provision and are geographically clustered by market.

Now, with an idea of the variation in the data, consider a consumer i in each of the twenty-four months t between January 2015 and December 2017. Each month, the consumer chooses one of the top four wireless postpaid service providers. That is, they either choose to stay with their current provider or switch to one of three competing alternative providers. At time t, consumer i chooses alternative j with the highest utility u_{ijt}. I specify consumer i's utility as

$$u_{ijt} = x_i\beta_j + \xi_{jmt} - c_{ijt} + p_{ijt} + \epsilon_{ijt} \tag{1}$$

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which depends on observable individual-level factors x_i, consumer i's unobservable idiosyncratic utility for alternative j, ϵ_{ijt}, and the product characteristics specific to alternative j in market m at time t, ξ_{jmt}. The last two elements of consumer utility measure switching costs and peer effects, respectively.

Consumers in the model face two switching costs. First, they incur a switching cost common to all consumers for each alternative j at time t, c^s_j, for all alternatives which are not their current service provider. Additionally, they face a learning cost c^l common to all consumers and each alternative j at time t. Consumers only face this cost once. For all months t after the time where a consumer has switched to alternative j, this cost is zero. Let $\mathbb{1}_s(j,i,t)$ be an indicator if alternative j is not a consumer's current provider at time t and $\mathbb{1}_l(j,i,t)$ be an indicator if alternative j is not in a consumer's purchase history before time t. Then, consumer i's switching costs are

$$c_{ijt} = c^s_j\mathbb{1}_s + c^l\mathbb{1}_l \tag{2}$$

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with one indicator for providers other than the consumer's current service provider and one indicator for providers with which the consumer does not have a prior history. In the model, the learning cost is common across alternatives, since it applies to all providers with which a consumer does not have a prior history. However, since the switching cost c^s includes a broader array of potential costs, from the cost of phones, to brand loyalty, or potential early termination fees, I allow c_j^s to vary across alternatives.

Next, I consider the peer effects p_{ijt}. As described by Angrist (2014) in a slightly different context, if we have a hypothesis that individual behavior is being influenced by peers in the same group, a natural formulation would be to model individual outcomes as being influenced by the average outcome in their group. In the context of a categorical choice, that means that the utility of consumer i for alternative j in market m might be influenced by alternative j's share, s_{jm}, in market m. So, when deciding which provider to choose, consumers might be influenced by impressions formed from interacting with other consumers, and the higher the share of those consumers in the market, the more opportunity there is for any particular consumer to be influenced. Angrist (2014) summarizes the main concern with an estimation of this sort as being 'vacuous,' in the same way that Manski (1993) noted that "...observed behavior is always consistent with the hypothesis that individual behavior reflects mean reference-group behavior." So, we might observe more consumers are likely to switch to the provider with the largest market share. However, this is almost certainly caused by the relevant product characteristics in the market which attracted both the providers' current consumers and continues to attract new consumers.

This is why the innovation by Bronnenberg et. al. (2013) of focusing on migrant consumers is helpful. Migrant consumers had an opportunity to be affected by peers in an entirely different market with a different set of product characteristics. So, if we observe migrant consumers are more likely to choose a provider with the largest market share in their home market, it is not because of the relevant product characteristics in their current market. It is this potential influence of market conditions from a market they are no longer a part of, and often for a provider they have no prior experience with, which I am discussing as a peer effect. Importantly, advertising and other ‘impressions’ consumers form would fall under this definition. My key identifying assumption is there are no other unobservable characteristics correlated with both a consumers’ home market shares, and the likelihood of choosing a particular provider, conditional on demographics, purchase history, and controlling for alternative-specific differences by market and time. Crucially, the last control rules out alternative-and-market specific product characteristics from the set of potential confounders.

However, it does not rule out all unobservable individual-level characteristics. As discussed above, unobservable individual-level differences clustered by market in a way generating between-market differences in market shares is a concern for identification. Angrist (2014) also considered this concern, noting estimated peer effects could actually “... reflect quotidian correlation in unobservables, in a world otherwise characterized by social indifference (p.10)." In estimation, alternative-specific fixed effects by market and time are an important control to addressing this concern. For instance, consumers who grew up in a rural area might be united in an unobservable preference for good network coverage. In turn, the largest market share would go to the provider with the best network coverage in that market. However, those who migrated to an area where a different provider has an advantage in network coverage would likely choose that provider, in a way consistent with the behavior of non-migrant locals. In addition, I test the robustness of my estimates to both changes in market definitions which distinguish migrants from non-migrants, and to the inclusion of different sets of individual-level controls.

Another complexity in looking at peer effects in these data involve the evolution over time. In the Bronnenberg, et al. (2013) formulation, peer effects arise as part of ‘brand capital,’ a stock of utility for each alternative which is a function of discounted past choices. They construct their measure of brand capital through the market share s_{jm} of choice j in market m, and estimate a discount rate. To put this another way, if we expect peer effects at time t have a lasting impact, it would diminish over time, as consumer discount old information or simply forget. Unfortunately, unlike that study, I do no observe the time since a consumer migrated, or if a consumer has migrated several times. This requires me to specify peer effects in a more reduced form,

$$p_{ijt} = \gamma_m s_{jmt} + \sum_{m'} \gamma_{m'} s_{jm't} \mathbb{1}_{m'} \tag{3}$$

,

where $\mathbb{1}_{m'}(i)$ indicates if consumer i migrated from market m'. There is no plausible way for me to separately identify the effect of unobservable current market product characteristics ξ_{jmt} and peer effects in the current market. So, in estimation I flexibly control for both with an alternative-market-time level fixed effect, θ_{jmt}, which estimates the total effect of all of the unobservable product characteristics of alternative j in market m at time t, including the 'characteristic' of peer effects on choosing j. However, I am able to estimate the long-term effects of a previous market on migrants, $\gamma_{m'} s_{jm't}$. My estimates for migrants are necessarily an average across consumers at different points in time in the depreciation of their 'brand capital'. So, it is a lower-bound on the effect without depreciation. Second, since I do not observe the time since a consumer migrated, I have to use current market shares in m' to stand-in for the past market shares in m'. The industry under study is uniquely well-suited to this modelling assumption. The most salient product characteristic in wireless service is network coverage, which requires costly and time-consuming physical investments in infrastructure. As discussed earlier, market shares change very little over time in the industry. Bronnenberg, et al. (2013) encounter a related problem, which they solve by assuming no product characteristics change over time.

With this model of consumer behavior and necessary assumptions, I estimate the extent of learning costs and peer effects, as described in the following section.

Estimation and Results

To indicate the robustness of my results to both specification choices, and the choice of market definitions, I present six specifications across three market definitions. All specifications include two sets of controls. First, all specifications include provider/market fixed effects by time, θ_{jmt}. Also, all specifications include a provider-specific indicator for alternatives which are not a consumer's current provider at time t, $\mathbb{1}_s(j, i, t)$. Across all specifications the two main variables of interest are an indicator for alternatives for which a consumer has no prior history $\mathbb{1}_l(j, i, t)$, and an alternative's market share in a migrant's home market $s_{jm't}$. These elements make up Specification (1),

$$\mu_{ijt} = \theta_{jmt} - c_j^s \mathbb{1}_s - c^l \mathbb{1}_l + \gamma_{m'} s_{jm't} \mathbb{1}_{m'} + \epsilon_{ijt} \tag{4}$$

.

For estimation, I assume ϵ_{ijt} follows an $i.i.d$ Type I extreme value distribution, so the likelihood of choosing alternative j can be estimated as a multinomial logit. This requires a standard normalization of μ to zero for one 'reference' alternative. The reference alternative for all estimates is Sprint Wireless, which has the fewest postpaid wireless subscribers. An important distinction in multinomial logit models is the distinction between generic coefficients which affect all the alternatives in the same way and alternative-specific coefficients which allow the effect to vary across alternatives. For instance, $\gamma_{m'}$ is a generic effect, where c_j^s is alternative-specific. All alternative-specific coefficients are interpreted relative to Sprint Wireless. I include a specification where I allow the effect of all key variables to be alternative-specific in order to determine any interesting differences across providers. The estimates are found with Maximum Likelihood using the Newton-Raphson method.[9]

[9] Asad Hasan, Zhiyu Wang, Alireza S. Mahani (2016). Fast Estimation of Multinomial Logit Models: R Package mnlogit. Journal of Statistical Software, 75(3)

Since unobservable individual-level variables are a particular concern in identification, specifications (2)-(4) introduce several dimensions of individual-level factors to indicate how robust estimates on the variables of interest are to individual-level variation. Specification (2) introduces a main effect on the indicator for consumer i's migration status $\nu_1 \mathbb{1}_{m'}(i)$, and specification (3) interacts migration status with the current provider effect $\nu_2 \mathbb{1}_{m'}(i)\mathbb{1}_s(j,i,t)$. Specification (4) includes demographic controls, x_i, consisting of age of head of household, log of household income, ethnicity of head of household, and household size. Specification (5) interacts consumer i's migration status with their prior history with a provider $\nu_{j3}\mathbb{1}_{m'}(i)\mathbb{1}_l(j,i,t)$. Since migration status is an alternative-specific effect, this interaction is also alternative-specific and no generic coefficient is reported. So, specification (5) with all individual-level controls is

$$u_{ijt} = x_i\beta_j + \theta_{jmt} - c_j^s\mathbb{1}_s - c^l\mathbb{1}_l + \nu_1\mathbb{1}_{m'} + \nu_2\mathbb{1}_{m'}\mathbb{1}_s + \nu_{j3}\mathbb{1}_{m'}\mathbb{1}_l + \gamma_{m'}s_{jm't}\mathbb{1}_{m'} + \epsilon_{ijt} \qquad (5)$$

.

Specification (6) includes all of the same factors in specification (5), but presents the alternative-specific estimates for migration status, home market share, and the interactions from specification (5). This last specification is only to indicate if any meaningful differences exist between alternatives on these key variables.

To provide a baseline on the relative likelihood of choosing various providers, recall the provider-reported information which indicates consumers switch between providers at low rates, generally less than 2% in any given month. That means the most natural way to express likelihood is in terms of a likelihood to switch, and a likelihood to remain. Across all specifications and market definitions, the results match provider-reported information well. The baseline likelihood for a consumer to switch, and choose any alternative which is not a consumer's current provider in a given month is between 1.79% and 1.93%. The baseline likelihood for a consumer to remain, and choose their current provider is between 98.21% and 98.07%. For a sense of scale, that rate corresponds to between one to two million consumers leaving each of the top four providers each month. The baseline likelihood for a consumer to switch, and choose a particular provider among the three alternatives which are not a consumer's current provider is near 0.59% for each alternative on average.

Across all the specifications and market definitions presented in Tables 6-9, the estimated multinomial log-odds on the indicator for having no prior history with a provider is between -0.72 and -0.77. This places a consumer's likelihood of switching to a particular provider they have no prior history with between 0.27% and 0.29%, with the likelihood of remaining with a provider the consumer has no prior history between 96.19% and 96.32%. That makes consumers around half as likely to switch to a provider with which they have no prior history, and only 98% as likely to switch away from a provider with which they have a prior history. These estimates are statistically significant at a 1% level. The estimated likelihood associated with market share in a migrant's home market varies more across specifications and market definitions. Before looking to any particular specification, its worth discussing how the different market definitions might affect those results. As discussed above, peer effects from a home market on migrants are necessarily mediated by the amount of time since the migrant left their home market, and I an unable to observe the time since a consumer migrated, or if they migrated more than once. In the extreme case in which all migrants moved immediately before January 2015, any impressions formed in a home market would have not depreciated at all. Since the peer effect from the home market would have not depreciated, we would expect the association with home market shares to be larger. In the other extreme case in which all migrants had left their home market in the distant past, the original home market peer effect on migrants would have depreciated, so we would expect it to be smaller, and a lower-bound on the effect for non-migrants. It is ambiguous how market definitions would affect the current market tenure composition of migrants, but one hypothesis would be the more granular the market definition, the larger portion of migrants who had moved recently. In fact, this is consistent with the results, in which the market definitions with more migrants (NPA and CMA) have a larger estimated effect than the state market definition.

Turning first to the NPA market definition in Table 6, the estimated multinomial log odds associated with each percentage point of market share in a migrant's home market is 0.0570 in specification (1). Consider an NPA migrant who has the choice of one provider whose market share was 10 percentage points higher in their home market. The estimated multinomial log-odds in specification (1) gives that consumer a likelihood of 1.04% to switch to that provider, and a likelihood of 98.98% of remaining with that provider. This makes consumers around 76% more likely to switch to the provider with the larger home market share. Although this estimate is robust to the inclusion of a migration indicator, introducing an interaction between a consumer's current provider and their migration status reduces the estimate to 0.0353, reducing the likelihood of remaining to 98.73%, and the likelihood of switching to 0.85%, only 44% more likely to switch. The estimate on home market share in specification (3) is robust to the inclusion of demographic controls in specification (4), and the interaction of migration and the indicator for no prior history with a provider in specification (5). In evaluating the extent to which individual-level unobservable characteristics might bias results, it is encouraging the only factor of observable individual-level characteristics biasing estimates in this market definition was the interaction between migration and alternatives which were not a consumer's current provider. If the relationship between migrants' home market shares and current likelihood to choose a provider were biased by unobservable individual-level characteristics, then the expectation would be observable individual-level factors would covary at least somewhat with the unobserved factors, and change the estimate on home market share when included.

Table 6: Multinomial Logit Results

NPA Level	(1)	(2)	(3)	(4)	(5)
No Prior History Indicator	-0.7431^{***}	-0.7434^{***}	-0.7463^{***}	-0.7459^{***}	
	(0.0534)	(0.0533)	(0.0542)	(0.0543)	
Home Market Share (1 percentage point)	0.0570^{***}	0.0543^{***}	0.0353^{**}	0.0354^{**}	0.0353^{**}
	(0.00851)	(0.00864)	(0.0115)	(0.0115)	(0.0116)
Provider/Market/Time FE	Yes	Yes	Yes	Yes	Yes
Not Current Provider Indicator	Yes	Yes	Yes	Yes	Yes
Migration Indicator	No	Yes	Yes	Yes	Yes
Migration/Not Current Provider Interaction	No	No	Yes	Yes	Yes
Demographic Controls	No	No	No	Yes	Yes
Migration/No Prior History Interaction	No	No	No	No	Yes
Observations	4,828,761	4,828,761	4,828,761	4,828,761	4,828,761

robust standard errors in parentheses

To provide a fuller view of how the key variables vary across alternatives, Table 7 presents the results of specification (6). These estimates include all of the controls from specification (5), but each estimate is alternative-specific. Importantly, this includes the effect of home market share which has a generic coefficient in specifications (1)-(5), and the interactions with migration, which have generic coefficients in specifications (1)-(4). All alternative-specific estimates are interpreted relative to Sprint Wireless. So, for instance, migrants were relatively more likely to choose Verizon Wireless, relatively less likely to choose AT&T Wireless, and relatively more likely to choose T-Mobile Wireless than Sprint Wireless in comparison to non-migrants. Although these effects are statistically significant, they are small in practical terms. Using those estimates, migrants are only 5% more likely to switch to Verizon Wireless, and 1.4% less likely to switch to T-Mobile Wireless. This indicates migrants do not have large differences in likelihood to choose any particular provider. Another variable with statistically significant alternative-specific results which are nevertheless practically insignificant is the estimated coefficients on home market share. The results indicate a 1 percentage point increase in home market share has a slightly higher association with the likelihood of choosing all three alternatives relative to Sprint Wireless, slightly more so for Verizon Wireless and AT&T Wireless than for T-Mobile Wireless. However, the effect size is not meaningful, corresponding with a less than 2% change in the likelihood of choosing any provider. In a similar way, alternative specific estimates on the interaction of migration with current provider and prior history are small in practical terms and statistically insignificant at a 5% level. These estimates do not add any qualitative information about important differences between providers, but as a robustness check confirm the variation described by key variables is not driven primarily by one or two providers.

Next, moving to the state market definition in Table 8, estimates on the effect of prior history on likelihood to choose a provider are very consistent with the estimates in the NPA definition. However, the estimated multinomial log-odds on a one percentage point increase in market share in a migrant's home market and current market is lower than in the NPA

Table 7: Multinomial Logit Results

NPA Level		(6)
Migration Indicator	Verizon Wireless	0.0397***
		(0.0069)
	AT&T Wireless	−0.0147***
		(0.0038)
	T-Mobile Wireless	0.0535***
		(0.0047)
Home Market Share (1 percentage point)	Verizon Wireless	0.0022***
		(0.0003)
	AT&T Wireless	0.0029***
		(0.0004)
	T-Mobile Wireless	0.0009***
		(0.0006)
Migration/Not Current Provider Interaction	Verizon Wireless	−0.0122
		(0.1049)
	AT&T Wireless	−0.1261*
		(0.0824)
	T-Mobile Wireless	0.0343
		(0.0670)
Migration/No Prior History Interaction	Verizon Wireless	−0.0393
		(0.0231)
	AT&T Wireless	−0.0365
		(0.0266)
	T-Mobile Wireless	0.0089
		(0.0140)
Observations		4,828,761

robust standard errors in parentheses

market definition, at 0.01976 in the specification (1). A state migrant who has the choice of one provider whose market share was 10 percentage points higher in their home state has a likelihood of 0.75% to switch to that provider, which is only 22% more likely to switch to that provider than baseline in specification (1). Much like in the NPA market definition, this estimate is lower when an interaction between migration and current provider is included, reducing the estimate to 0.67%, at 13% more likely. As also was the case under the NPA definition, this estimate is robust to the inclusion of demographic variables, the indicator for migration, and the interaction between migration and prior history. The state market definition results for specification (6) presented in Table 9 are also consistent with the NPA results. None of the key variables had meaningfully significant alternative-specific differences, even where some are statistically significant.

Table 8: Multinomial Logit Results

State Level	(1)	(2)	(3)	(4)	(5)
No Prior History Indicator	-0.7281^{***}	-0.7289^{***}	-0.7267^{***}	-0.7303^{***}	
	(0.0529)	(0.0520)	(0.0534)	(0.0533)	
Home Market Share (1 percentage point)	0.01976^{***}	0.01923^{***}	0.0130^{***}	0.0138^{**}	0.0139^{**}
	(0.0026)	(0.0027)	(0.0029)	(0.0115)	(0.0116)
Provider/Market/Time FE	Yes	Yes	Yes	Yes	Yes
Not Current Provider Indicator	Yes	Yes	Yes	Yes	Yes
Migration Indicator	No	Yes	Yes	Yes	Yes
Migration/Not Current Provider Interaction	No	No	Yes	Yes	Yes
Demographic Controls	No	No	No	Yes	Yes
Migration/No Prior History Interaction	No	No	No	No	Yes
Observations	4,828,761	4,828,761	4,828,761	4,828,761	4,828,761

robust standard errors in parentheses

Table 9: Multinomial Logit Results

State Level		(6)
Migration Indicator	Verizon Wireless	0.0487***
		(0.0095)
	AT&T Wireless	−0.0317**
		(0.0111)
	T-Mobile Wireless	0.0459***
		(0.0095)
Home Market Share (1 percentage point)	Verizon Wireless	0.0025***
		(0.0006)
	AT&T Wireless	−0.008***
		(0.0007)
	T-Mobile Wireless	0.0005***
		(0.0006)
Migration/Not Current Provider Interaction	Verizon Wireless	−0.1258
		(0.1156)
	AT&T Wireless	−0.3525*
		(0.0111)
	T-Mobile Wireless	−0.0625
		(0.0065)
Migration/No Prior History Interaction	Verizon Wireless	−0.0086
		(0.0433)
	AT&T Wireless	0.0340
		(0.0449)
	T-Mobile Wireless	0.0241
		(0.0285)
Observations		4,828,761

robust standard errors in parentheses

The last market definition to consider is CMA, in Table 10. As noted at the beginning, the estimated effect of having no prior history with a provider is consistent with results from the other market definitions. The estimate in Table 10 indicated consumers were roughly half (46%) as likely to switch to a provider they have no prior history with, and 97.93% as likely to switch away from a provider with which they have a prior history. The estimate for home market share is 0.0382 in specification (1), which corresponds to a 34% higher likelihood to switch to a provider with a 10 percentage point higher market share in a migrant's home market. As in other market definitions, results for specification (6) presented in Table 11 indicate key variables had meaningfully significant alternative-specific differences.

Table 10: Multinomial Logit Results

CMA Level	(1)	(2)	(3)	(4)	(5)
No Prior History Indicator	-0.7773^{***}	-0.7775^{***}	-0.7781^{***}	-0.7771^{***}	
	(0.0565)	(0.0553)	(0.0569)	(0.0569)	
Home Market Share (1 percentage point)	0.0382^{***}	0.0376^{***}	0.0294^{**}	0.0292^{**}	0.0292^{**}
	(0.0085)	(0.0086)	(0.0090)	(0.0091)	(0.0091)
Provider/Market/Time FE	Yes	Yes	Yes	Yes	Yes
Not Current Provider Indicator	Yes	Yes	Yes	Yes	Yes
Migration Indicator	No	Yes	Yes	Yes	Yes
Migration/Not Current Provider Interaction	No	No	Yes	Yes	Yes
Demographic Controls	No	No	No	Yes	Yes
Migration/No Prior History Interaction	No	No	No	No	Yes
Observations	4,828,761	4,828,761	4,828,761	4,828,761	4,828,761

robust standard errors in parentheses

Table 11: Multinomial Logit Results

CMA Level		(6)
Migration Indicator	Verizon Wireless	0.0365***
		(0.0054)
	AT&T Wireless	0.0316***
		(0.0061)
	T-Mobile Wireless	0.0624***
		(0.0053)
Home/Current Market Share Difference	Verizon Wireless	0.0020***
		(0.0003)
	AT&T Wireless	0.0029***
		(0.0004)
	T-Mobile Wireless	0.0012***
		(0.0005)
Migration/Current Provider Interaction	Verizon Wireless	0.0002
		(0.0694)
	AT&T Wireless	−0.1321*
		(0.0796)
	T-Mobile Wireless	0.00397
		(0.0562)
Migration/Prior History Interaction	Verizon Wireless	−0.0217
		(0.0221)
	AT&T Wireless	−0.0463
		(0.0238)
	T-Mobile Wireless	0.0187
		(0.0140)
Observations		4,828,761

robust standard errors in parentheses

Discussion

The results across specifications and market definitions consistently indicate a strongly reduced likelihood of choosing a service provider a consumer has no prior experience with, and a slightly higher likelihood for migrant consumers in choosing a service provider with a higher market share in their home market. The former result is consistent with consumer behavior under learning costs. If consumers already know the quality level of a provider from first-hand experience, that makes them less likely to choose other providers which they are more uncertain about. The latter result is consistent with other studies inidicating peer effects in this market (Han and Ferreira, 2014). Although observed in migrant consumers, the robustness of the results, and comparability of migrant and non-migrant consumers indicate that these peer effects are likely for a broad range of consumers.

Another important question of these results is how generalizable they might be across other industries. When Bronnenberg, Dubé, and Gentzkow (2012) conducted their study in the packaged goods market, they found a large effect for long-term brand preferences. Since their data do not allow breaking out 'brand capital' into switching costs, learning costs, peer effects, advertising, or other factors it is difficult to know if their results also are consistent with large learning costs and a small but positive effect for peers and advertising. However, it is not unlikely that in many other markets consumers both face learning costs associated with the uncertainty of product quality, and form long-term brand impressions.

Taken together, learning costs and peer effects are two sources of market power for wireless service providers. Firms in the wireless service provision market can count on consumers' relative uncertainty of the quality of other alternatives attracting current and former consumers, and success in any market being re-enforing, as both a firm's own consumers, and peers of those consumers form positive impressions that are long-lasting. Notably, these are additional elements of market power above and beyond switching costs from 'locked' phones, early termination fees, or from regulation (Faccio and Zingales, 2017). In an industry where the effects of consolidation is consistently of interest to regulators, these less-studied sources of market power are important to consider.