COMPETITION IN NETWORK INDUSTRIES: EVIDENCE FROM MOBILE TELECOMMUNICATIONS IN RWANDA

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This paper develops a method to analyze the effects of competition policy in a network industry. I estimate the network utility of adopting a phone based on its subsequent usage, using transaction data from nearly the entire network of Rwandan mobile phone subscribers over 4.5 years, and the method of Bjorkegren (2018). I extend that method to simulate the equilibrium choices of consumers and network operators. The Rwandan government waited to promote competition. I find that adding an additional competitor earlier would have reduced prices and mostly *increased* incentives to invest in rural towers, increasing welfare by the equivalent of 1.4% of GDP. When the network is split with a competitor, the incumbent would have captured only a fraction of the network effects generated by investment, but this effect is dominated by an increased incentive to differentiate its coverage. I analyze the effects of setting different interconnection rates, and reducing switching costs through number portability.

JEL Classification Codes: O33, L96, O180, L51

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1. Introduction

Many modern technologies have network effects, and as a result lead to industries with natural monopolies. How should societies manage these industries?

Historically, the question of how to manage network industries has not extended much further than the technologies themselves (consider AT&T in telecommunications or Microsoft in operating systems). However, as software has become more embedded in the economy, it has generated network effects in disrupted industries. As a result, this question is becoming increasingly central across the economy (how should societies manage Facebook, which has reshaped the media industry, or emerging networks like Uber, which some are betting will find itself the central network for coordinating urban transportation?).

One approach would accept that market forces will exert limited discipline on network industries, and rely on the government to intervene when a firm steps out of bounds. But it is not clear how to draw these bounds. These industries change rapidly: boundaries that might have been drawn for Facebook in 2005 would be irrelevant today.[1] And reactive interventions introduce uncertainty, and are likely to be sensitive to whichever public relations scandal has captured recent public attention, rather than underlying structural issues.

Alternatively, if consumers could choose between networks, competition could discipline the industry. But choice seldom arises in these markets naturally, because it is difficult to compete with an incumbent network.[2] To spur choice, governments can tilt the playing field, by forcing an incumbent to connect its network to entrants (as in telecom, where typical regulations guarantee that consumers can call subscribers of competing networks), or making it easier to switch (e.g., allowing consumers to take their data or account to a different network). Or, governments can split up a dominant firm (as was done with AT&T or debated with Microsoft).

[1] Likewise, Microsoft's dominance in desktop operating systems matters much less today, now that computing has shifted towards mobile and web.

[2] This was a central concern in congressional interrogation of Facebook: Senator Lindsey Graham asked: 'If I buy a Ford, and it doesn't work well, and I don't like it, I can buy a Chevy. If I'm upset with Facebook, what's the equivalent product I can go sign up for?'

However, if societies impose too much discipline, or exert discipline in the wrong ways, firms may decide not to make the large investments needed to build these networks. In particular, competition splits the network between firms, so that each internalizes only a fraction of network effects. How, and how strongly, should societies discipline emerging network industries?

While theory outlines the contours of tradeoffs in markets with classical network effects, there is little empirical work to guide policy choices.[3] This paper develops an approach that uses data to quantify how discipline affects investment and welfare.

The most straightforward empirical approach would compare outcomes of isolated networks in jurisdictions that set different policies. For example, in cross country panels, Faccio and Zingales (2017) and Genakos et al. (2018) find that increases in telecom competition are associated with price reductions. However, it is not clear how to interpret reduced form results. Firms choose prices and investments in anticipation of future policy changes: depending on these expectations, a reduced form approach could suggest wildly different impacts of the same policy. And this approach would not be helpful for the most dominant modern networks, which dominate across countries: there's only one Facebook, and one Google.

This paper instead computes investment incentives directly, by modeling firm objective functions with a structural approach. Classical network goods like telephones become more useful when others adopt. As a result, each individual's demand is a function of the demand of others in the network. Estimating this network demand introduces three issues. First, one needs to measure the entire network in order to estimate demand, and how the benefits of investments spill over across subnetworks. As a result, it is typically not possible to study competitive markets directly: when the market is split, network data would need to be obtained from all competitors and linked at the node level.[4] Second, even if one had this data, it is difficult to identify

[3]See Katz and Shapiro (1994) and Farrell and Klemperer (2007) for review articles. This paper studies classic network goods, whose value depends directly on the network of other users. Conceptually related are goods with indirect network effects, such as platforms and video formats (Ohashi 2003; Gowrisankaran et al. 2010; relatedly, Lee 2013): popular platforms tend to be better served by sellers, so adopters benefit indirectly from additional users.

[4]The actual network of users matters even for many goods where network effects are indirect—for example, dynamic carpooling services like Uber Pool become more useful when others traverse your same route; Tesla's autopilot learns from other Teslas that drive your same roads.

network effects: one individual may adopt after a contact adopts because the contact provides network benefits, or because connected individuals share similar traits or are exposed to similar environments. And finally, if these two issues are overcome, it is difficult to compute equilibria: firms must anticipate how their actions ripple through the entire network of demand, and affect their stream of profits into the future.

This paper overcomes these challenges in the context of developing country mobile phone networks, which account for 2.5% of GDP in sub-Saharan Africa (GSMA, 2018). As in Bjorkegren (2018), I study Rwanda's mobile phone network during a period of rapid expansion, using 5.3 billion transaction records from the dominant mobile phone operator, which held over 88% of the market.

My empirical approach has four parts:

First, acknowledging that the utility of owning a mobile phone is derived from its usage, I model the utility of using a phone, using the method and estimates of Bjorkegren (2018). As of this writing, only 9% of mobile phones in Rwanda are smartphones (ResearchICTAfrica, 2017), and in the period I study almost all phones were basic mobile phones. I infer the value of each voice connection from subsequent interaction across that connection. This approach bypasses most of the simultaneity issues that result from inferring value from correlations in adoption. A subscriber must value a connection at least as much as the cost of calls placed across it.[5] And 99% of accounts are prepaid: the person placing a call pays for it on the margin, by the second.[6] Because the firm changed calling prices and increased the quality of coverage, I can identify the underlying demand curve for communication across each link.

Second, I model the decision to adopt a mobile phone and operator. The utility of having a phone in a given period is given by the utility of communicating with contacts that have phones. Consumers choose when to adopt by weighing the increasing stream of utility from communicating with the network against the declining cost of purchasing a handset. (This approach has parallels with Ryan and Tucker (2012),

[5]In contrast, most empirical studies of network goods use coarse measures of the value of joining the network; exceptions that use individuals' local network are Tucker (2008) and Birke and Swann (2010).

[6]In the first 14 months of the data, calls are billed by the first minute and every following 30 seconds.

which analyzes adoption of a videoconferencing system from its use. But in that context, individuals face no cost of use or adoption.) I extend Bjorkegren (2018) to allow consumers to select and switch between operators, which may offer different price and coverage paths. Consumers value the coverage around the geocoordinates where they, and their contacts, use their phones. Thus, the interactions between geographical coverage and social network drive consumer choices between operators, which define how the network will be split under competition. Because choices between operators are not observed in a monopoly environment, I pose hypothetical questions to Rwandan consumers to estimate switching costs and idiosyncratic preferences for the entrant. I corroborate these estimates using an additional validation choice that mimics a real choice made in my data (the choice of plan).

Third, I model firm decisions. As a condition for receiving a license, the Rwandan regulator required firms to submit a 5 year network rollout plan, specifying which geographical locations to build towers at which times. I require firms to commit to a network rollout plan and a path of calling prices for the period of interest at the beginning of the license period. To limit the multiplicity of equilibria, I require that firms charge the same rate for on- and off-network calls. These restrictions represent feasible terms of competition that could be implemented by the regulator, so my results will represent a lower bound on the benefits that could be achieved under more general terms. To evaluate the cost of expanding or shrinking the network, I use engineering cost data, which was collected under mandate by the regulator.

Fourth, to evaluate the impact of policies, I use a simulation method that allows each individual to react directly to a change, and to each other's responses, capturing effects that ripple through the network and across physical space. An equilibrium in this context must reconcile firm pricing and rollout decisions with nearly 1 million interconnected adoption decisions. To make simulation tractable, I compute an adoption equilibrium in publicly announced adoption dates, as in Bjorkegren (2018). I bound the full set of equilibria by exploiting the supermodularity of the adoption decision, in a manner similar to Jia (2008). Competitive conditions can break supermodularity, because consumers trade off prices and quality. I bound adoption equilibria in two steps: by first simulating an adoption quasiequilibrium using the

upper (or lower) envelope of prices and quality; and then from this quasiequilibrium simulating an adoption equilibrium. I compute a full equilibrium by letting firms iteratively best respond against each other, anticipating resulting adoption equilibria, until reaching a fixed point. To reduce the computational burden, I let the grid of strategies become adaptively refined.

In resulting equilibria, a monopolist will internalize demand spillovers within the entire network; when the network is split by competition, a firm will internalize only the spillovers within its own network. Network effects, and thus firm incentives, depend on network structure. For example, if only rural consumers directly benefit from a rural investment, and rural consumers are only connected to other rural consumers, it will not have spillovers on the urban network. Because I model the full structure of the network, my results factor in the position of each node in the network and will correctly capture these effects.

The resulting method can be used to evaluate the effect of a wide class of policies, including adding an entrant or breaking up the incumbent; changing the cost of switching operators; requiring networks to interconnect under rates which can be arbitrarily sophisticated; directly regulating coverage or the price of calls; and changing taxes on handsets and airtime.

Because my approach only requires data from an incumbent monopoly, it can be used by a regulator to evaluate the central question in many markets: what is the impact of tilting a monopolized network industry towards competition? It is particularly well suited to testing one of the most common incumbent objections: that sunk investments would have been made only in anticipation of maintaining control of the network.

This approach has limitations. In particular, the network is illuminated by adoption and usage, so individuals who do not adopt under monopoly provision are omitted. Counterfactuals that make the network more attractive could cause these individuals to adopt earlier. I model the behavior of nodes in this 'dark' portion of the network, and report results for shorter time horizons before these nodes would have adopted.

The details of competition policy have been 'a main bottleneck' in the development of African telecom markets (World Bank, 2004). Voice still accounts for the majority of mobile phone revenues in developing countries (60% of the incumbent parent's African revenue in 2017), but these networks provide a platform for an emerging stack of services that are reshaping developing economies.[7] Mobile phones are the primary mode through which Africa accesses the internet, but it will take substantial investments in towers to reach the one third of the population that lacks data coverage (GSMA, 2018). In Rwanda, the internet is used by only 8% of people, and 3% in rural areas (ResearchICTAfrica, 2017).[8] Mobile money has been extraordinarily successful in Kenya and has enabled a revolution in consumer finance (Bjorkegren and Grissen, 2018). However, that success has proven difficult to replicate: Safaricom may have made large investments to scale M-PESA only because it had no effective competitors in the voice network.[9] The tension between investment and discipline has made telecom competition policy hotly contested: regulators that heavily pushed competition are now deciding how to manage increasing calls for consolidation (Moody's, 2015).

Telecom has been a classic case study for network effects, and there is extensive theoretical work on competition policy for developed country landline networks (Armstrong, 1998; Laffont et al., 1998; Laffont and Tirole, 2001). However, it can be inconclusive (Vogelsang, 2013), and was developed during the liberalization of established networks, so mostly omits factors that are important for growing networks, such as investment and network effects (with some exceptions, Valletti and Cambini, 2005). As a result, it provides limited guidance for developing country mobile networks.

Rwanda is a convenient setting to study these dynamics. Rwanda initially limited competition to encourage investment, providing a monopoly license to my partner operator until 2005. I study the following period of contested monopoly from 2005-2009, during which the regulator allowed the entry of a competitor that was mismanaged.

This contested monopoly period has three useful features. First, the incumbent lowered prices after the contester's entry, so I observe demand under substantial

[7]Revenue figure includes two small operations outside of Africa.
[8]See A2 for mobile internet coverage over time in Rwanda.
[9]Indeed, across countries, telecom competitiveness is negatively correlated with the density of mobile money agents.

variation in price. But second, because that entrant never attained significant market share, the incumbent's data describes nearly the entire network of mobile phone owners at the time. This allows me to measure how effects would ripple through nearly the entire network had it been split with additional competitor. Third, in this period, the incumbent made large investments in coverage, nearly quadrupling the number of towers and increasing coverage from 60% to 95% of land area. In my counterfactuals I will hold fixed the network and behavior of the poorly performing entrant and evaluate the effect of increased competition in the incumbent network. For convenience, in the rest of the paper I refer to this baseline market structure as monopoly.

After this period, the regulator granted an additional license to a well managed competitor, which built out less coverage, charged lower prices, and captured market share. If this additional competitor had been granted a license earlier, how would the industry have developed? Would coverage still have expanded into rural areas?[10]

I find the following:

Even in this early stage of the network, at baseline the incumbent's mobile phone system provided net social welfare of $334-$386m, an amount equivalent to 2-3% of Rwanda's GDP over the same period.

Adding a competitor under the government recommended rate would have dramatically lowered calling prices: the entrant would have charged 35% of the monopoly rate, and the incumbent 45%, charging a premium for its better coverage. On net, adding a competitor under the government's suggested interconnection rates would have increased the net welfare provided by the mobile phone system by up to 60%, an amount equivalent to 1.4% of GDP or 6-7% of official development aid over this time period. Results are similar if the monopoly directly charged the prices that were eventually charged under competition.

This suggests that the industrial organization of emerging networks can have profound welfare implications for the world's poorest economies.

[10]The optimal market structure remains an open question: in 2011, the second operator's license was revoked and its assets were sold to a fourth firm. In 2018, that firm merged with the third firm, bringing the industry back to a duopoly.

Adding a competitor would have also altered the incumbent's incentives to invest in rural towers. I quantify three forces in simulations. First, lowered prices reduce the total revenue from investing in rural towers by 22-25%. Second, when the network is split, 15-16% of the resulting total accrues to the entrant. The entrant pays the incumbent 10% back in interconnection fees, to account for increased usage of its network. In isolation, these two forces would make it unprofitable to build a substantial set of rural towers. However, they are dominated by a third force, a business stealing effect, which accounts for 83-85% of the revenue the incumbent earns from building the rural network. Building out rural coverage allows the incumbent to attract the set of marginal urban subscribers who wish to use phones in rural areas but would otherwise subscribe to the lower priced operator. The balance of these forces depends on the interconnection rate; under the government's suggested rate, adding a competitor would have *increased* incentives to invest in rural towers. This result is foreshadowed by a decomposition of baseline monopoly simulations which find that a large fraction of the revenue generated by rural towers arises from urban consumers who value rural coverage.

I find that competition would have been unlikely to develop in absence of interconnection regulation. If the incumbent chose the terms of interconnection and the regulator required operators to charge the same price for on- and off-net calls, the incumbent would have effectively blocked access to its network. This echoes what is seen in many network industries that do not endogenously develop compatibility (Katz and Shapiro, 1985).

I also find that the particular rules that the regulator selects for the competitive environment can also have substantial welfare consequences. Theory suggests that compatibility can reduce competition in early stage network industries, but can increase competition in mature networks (Katz and Shapiro, 1986). I evaluate a range of interconnection rules, including rules that treat the operators asymmetrically; lowering the interconnection rate tends to intensify price competition. Different reasonable interconnection regimes produce a difference in net social welfare equivalent to 0.3% of GDP over this period.

Theory suggests that switching costs can have ambiguous effects: they can help cement an incumbent's lead, or allow an incumbent to more easily coexist with rivals by inducing it to focus on its locked in consumers (Farrell and Shapiro, 1988; Suleymanova and Wey, 2011; Chen, 2016). I evaluate a number portability policy which reduces the cost of switching by allowing consumers to transfer their phone numbers. I find that it would have shifted a small amount of subscribers and profits to the entrant and slightly increased welfare.

The next section describes the development of competition in mobile phone networks worldwide and in Rwanda. Section 3 describes the data. Section 4 presents a model of phone adoption and usage. Section 5 describes estimation, Section 6 describes simulation, Section 7 presents monopoly benchmarks, Section 8 describes the applicability of the model to competition, and Section 9 describes the results of introducing competition. Section 10 concludes.

2. Context

Developing country phone systems. Between 2000 and 2011, the number of mobile phone subscriptions in developing economies increased from 250 million to 4.5 billion (ITU, 2011). Handsets were initially expensive, but became accessible even to the poor as component costs decreased. In 2005, the cheapest mainstream handset in Rwanda cost roughly $70, or 3.5 months of the mean person's consumption; by 2009 handsets were available for $13. As poor consumers began to be able to afford phones, operators developed prepaid plans that charge only on the margin, and invested in coverage in increasingly remote regions.

As these networks grew, regulators began to grapple with managing the emerging industry. Because cellular signal blankets an entire area, it is feasible to reach the same household with multiple wireless networks. As a result, competition can take more flexible forms than with landline networks. Countries quickly realized that it may be possible to obtain better performance from the sector by allowing multiple operators to compete in providing service to end users.

However, an entrant phone network will be of limited use unless it can connect to the incumbent phone system. Left to the market, incumbents typically demand

prohibitively high fees for interconnection, preventing competition (the 'one way' access problem). Thus, regulators typically intervene and determine the terms of interconnection. When network sizes are balanced, theory suggests that the problem is lessened (the 'two way' access problem) but ongoing regulation is required, since negotiated interconnection rates can be an instrument of collusion (Armstrong, 1998; Laffont et al., 1998). Theory suggests that interconnection rates should be set to a function of the cost of connecting a phone call, and the World Bank (2004) model for calculating these costs is used as a benchmark in many countries. But different theoretical models suggest different optimal interconnection rates, and the regulator must continually decide which direction to tilt competitive favor. Additionally, most telecom theory is designed for mature developed country networks, and thus does not consider how policies affect growth of the network. Network effects are much more important in developing country systems, because most people adopting phones are new adopters. And network effects have become more important, because modern handsets can interact with new network services (such as mobile money and Uber).

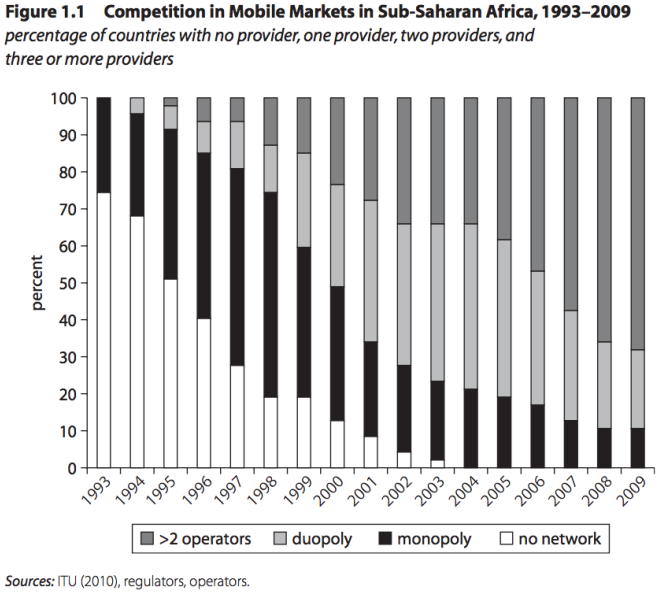
Thus, developing societies face two large questions: how much competition should regulators promote? And how should regulators shape the competitive landscape?

After resolving initial interconnection disputes, most countries have slowly invited competition (see Figure 1), first over voice service and then over new services like data. But there have been increasing calls for consolidation; and in East Africa between 2010 and 2015, only one country saw net entry of a telecom operator while three countries had net exit.

There is also little consensus on the optimal ground rules for competition. Table 1 summarizes current industry statistics and regulations in sub-Saharan Africa. While most countries regulate retail and interconnection prices, they consider different information to determine levels, and allow different amounts of complexity.

Rwanda. In the aftermath of the 1994 genocide and civil war, the Rwandan government worked to develop a mobile phone system. In 1998 it granted a license to a multinational to develop and run a network (Operator A); it was understood that this license would be exclusive for a limited period of time. In 2003, the government announced it would provide a license to a second operator, which entered the market

FIGURE 1. Telecom Competition



Source: Williams et al. (2011)

in 2005 (Operator B). The second operator sought to connect its network to the first; the resulting dispute over interconnection was "the major problem" at the regulatory agency at the time (RURA, 2005, 2006). In 2006, a consultant was hired to implement the World Bank Long Run Incremental Cost model. Despite the resolution of the interconnection dispute, this second operator was troubled and unsuccessful: after several changes in ownership (including by part of the Libyan government) it aggressively lowered prices and reached a maximum of 20% of market share for a brief period after the end of my data, and in 2011 its license was revoked for failure to meet obligations.[11] In an effort to push competition, the Rwandan regulator granted a license to a third operator (Operator C), which entered the market at the end of 2009 with aggressive promotional prices as it rolled out a network. See Figure 2a for the evolution of on-network prices in Rwanda.

[11]The Registrar General, Louise Kanyonga said, "The company was mismanaged and their liabilities far outweigh their assets... This has been a real learning experience for our government. We need to ask how this happened."

TABLE 1. Mobile Telecommunications in sub-Saharan Africa

Industry Statistics (2015 or latest available)	Mean	SD
Number of operators	3.27	1.48
Top market share	0.58	0.19
Second highest market share	0.32	0.09
Market concentration (HHI)	0.49	0.21
Regulations*		
Retail prices are regulated	89%	
...based on costs	43%	
...based on benchmarks	38%	
Interconnection charges are regulated	97%	
...based on costs (LRIC or FDC)	71%	
...based on benchmarks	43%	
...asymmetrically between operators	31%	
...using multiple zones	34%	
...using multiple timebands	56%	
Infrastructure is shared	100%	
...by mandate	62%	
...including active infrastructure (electronics)	48%	

Industry statistics from 2015 or latest year available, source: regulator reports and news articles. *Regulation statistics from 2015, for all SSA countries with available regulatory data (ranges from 21 to 41 countries depending on question), source: ITU.

As Operator C rolled out its network, the Rwandan government wanted to avoid duplication of infrastructure. It required operators to share infrastructure when possible, by allowing others to install equipment on their towers, at prices set by the owning network. In response to a dispute between Operators A and C, the government conducted a cost study and, controversially, required operators to share infrastructure at cost (RURA, 2011). The ex post sharing mandate allowed new operators to expand their networks much more quickly but Operator A expressed concerns that it violated expectations and could chill future investment. When the next round of infrastructure was rolled out, the government used a new, ex-ante sharing model: it granted a license to a South Korean firm to build a single, wholesale 4G network, which was leased out to the operators.

In 2011 a license was granted to Operator D, which purchased the assets of the Operator B and took over its license. After a second interconnection dispute, the regulator again hired a consultant, who gathered detailed cost data from operators and based on a model of the cost structure, recommended lowering interconnection rates along a glide path (see Argent and Pogorelsky, 2011; RURA, 2009).

In 2018, Operator C and D merged, bringing the market back to a duopoly.

See Figure 2 for the evolution of handset prices, accounts, calling prices, and coverage. The coverage plot shows that despite being able to build on the incumbent's towers, entrants' networks offer less complete coverage. The calling price plot shows the baseline calling price, and foreshadows the result of a focal counterfactual where Operator C is granted a license in 2005 at an analyst recommended interconnection rate of $0.07 per minute.

Consumer choice. The ability of competition to discipline firms depends on how consumers choose between products.

Table 2 shows the results of a Research ICT Africa survey of phone owners in several sub-Saharan African countries. During the period I study, most accounts are prepaid, so I will consider the handset market as separate from the market for phone plans. During this period, phones were used primarily for voice calls, so I focus on voice calls between the primary operator's subscribers. I do not explicitly model utility from SMS, missed calls, international calls, and calls from payphones.[12] Any value these omissions provide to the primary operator's subscribers will be captured in a residual when I estimate the adoption decision.

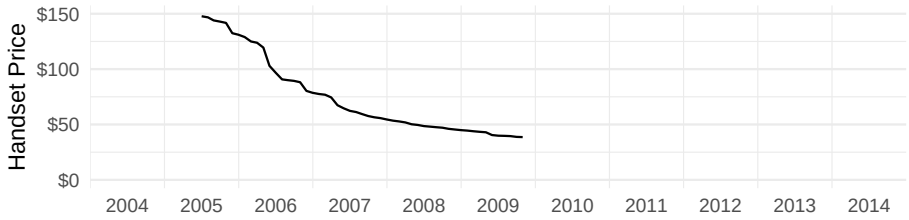
Consumers report selecting operators mostly based on coverage (51% of respondents, multiple responses allowed), which network their contacts are on (37%), the range of services offered (27%), and price (20%).[13] I develop a model to capture the

[12]From the data it is not possible to match the sender and receiver of a given SMS. Though important in other contexts, in Rwanda text messaging or SMS was high priced ($0.10 per message) and represented less than 13% of revenue and 16% of transactions. Only calls that are answered incur a charge; so subscribers may communicate simple information with missed calls (Donner, 2007). But it is difficult to distinguish between missed calls that provide utility (communicating information) and those that provide disutility (due to network problems or inability to connect).

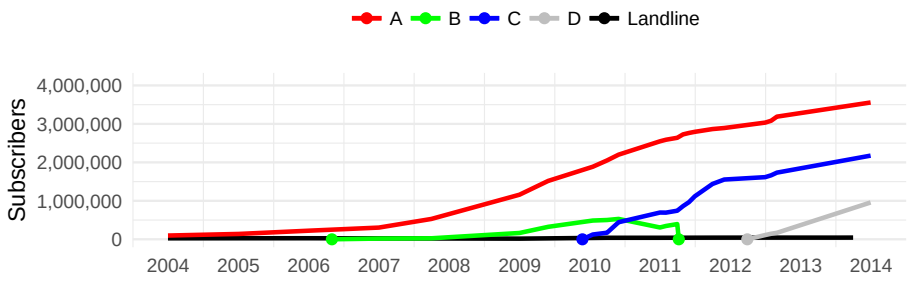
[13]See Table A1 for the full responses to these differentiators.

FIGURE 2. Development of Telecommunications in Rwanda

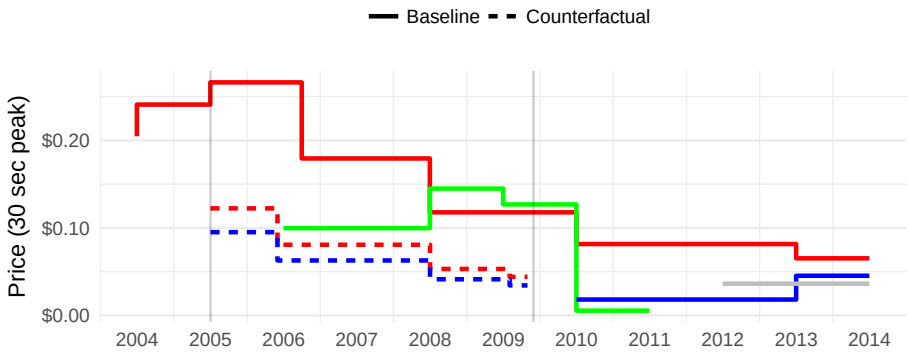
(a) Handset Price (real, quality adjusted index)



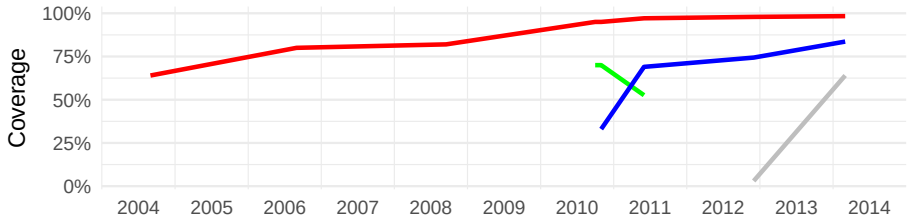
(b) Accounts



(c) Calling Price, On Network (30 second peak call, nominal)



(d) Coverage (geographic)



Handset prices reported during the years I have data on prices and quantities. I report baseline calling prices and the prices from a focal counterfactual where Operator C enters in 2005 with an interconnection rate of $0.07 per minute.When the market was essentially a monopoly the number of accounts corresponded closely to the number of individuals with phones. Under competition, some individuals held accounts with multiple operators so that there are more accounts than phone owners (in a 2010-2011 survey, 36.9% of individuals with phones have multiple accounts (RIA, 2012)). Sources: archived operator websites and regulator reports.

TABLE 2. Mobile Phone Usage among Owners in sub-Saharan Africa

	2007-8		2010-11	
	Rwanda	SSA**	Rwanda	SSA*
Received phone with a contract	0%	3%	3%	11%
Use phone for				
Voice calls	95%	98%	100%	99%
Music or radio	6%	14%	35%	46%
Taking photos or videos	5%	15%	24%	39%
Email	2%	3%	13%	14%
Sending or receiving money	-	-	18%	18%
Browsing Internet	-	-	15%	17%
Facebook or other social network	-	-	14%	16%
Apps (downloaded)	-	-	6%	15%

Source: RIA household surveys 2007-2008 and 2010-2011. *: Representative samples of mobile phone owners in Cameroon, Ethiopia, Ghana, Kenya, Mozambique, Namibia, Nigeria, Rwanda, South Africa, Tanzania, and Uganda; **: also Benin, Botswana, Burkina Faso, Cote d'Ivoire, Senegal, and Zambia. A dash indicates that question was not asked in that survey round.

key differentiators (coverage and pricing). In my model operators will not differentiate on services as there was little scope for this in Rwanda at the time.

3. DATA

This project uses several data sources (for more information see Appendix B):

Call detail records: As a side effect of providing service, mobile phone operators record data about each transaction, called Call Detail Records (CDRs). This project uses anonymous call records from the dominant Rwandan operator, which held above 88% of the market during this period. This data includes nearly every call, SMS, and top up made over 4.5 years by the operator's mobile phone subscribers, numbering approximately 400,000 in January 2005 and growing to 1.5 million in May 2009. For each transaction, the data reports: anonymous identifiers for sender and receiver, corresponding to the phone number and handset, time stamps, the location of the cell towers used, and call duration.[14] I aggregate durations to the monthly level.

[14]Some months of data are missing; from the call records: May 2005, February 2009, and part of March 2009. The locations of 12% of tower identifiers are missing from this data; I infer their location based on call handoffs with known towers using a procedure I have developed (Bjorkegren, 2014).

Operator costs: Like many telecom regulators, the Rwandan regulator requires that operators interconnect their networks, under charges 'derived from relevant costs' (RURA, 2009). Because the determination of these rates are crucial to competitive interactions in the market, the regulator collects cost data from operators and cross-checks these against regional and international benchmarks. To compute the cost of operating networks of different scales, I use long run incremental costs derived from a Rwandan study completed by international consultants (PwC, 2011).

Coverage: A rollout plan, $\mathbf{z} = \{(t_z, x_z, y_z)\}_z$, is defined by tower build dates and geographical coordinates. I consider the baseline rollout, $\mathbf{z}_{full}$, as well as counterfactual rollouts that trim low revenue rural towers. I create coverage maps by computing the areas within line of sight of the towers operational in each month, a method suggested by the operator's network engineer. Elevation maps are derived from satellite imagery recorded by NASA (Jarvis et al., 2008; Farr et al., 2007).

Individual locations and coverage: Because handsets are mobile, an individual may make calls from several locations, such as a village and the capital. I infer the geographical coordinates of each subscriber i's set of most used locations, $\{(x_{il}, y_{il})\}_l$, based on their eventual calls, using an algorithm analogous to triangulation (a version of Isaacman et al. (2011) that I have modified to improve performance in rural areas). Because individuals may use the phone in the area surrounding each location, I compute a smoothed coverage map, where $\phi_t(x, y; \mathbf{z})$ represents an average of the coverage available near (x, y) under rollout plan $\mathbf{z}$, weighted by a two-dimensional Gaussian kernel with radius 2.25km. I compute an individual specific coverage sequence by taking the average of the coverage at each individual's important locations weighted by the days spent at each location, d_{il}: $\phi_{it}(\mathbf{z}) = \frac{\sum_l \phi_t(x_{il}, y_{il}; \mathbf{z}) \cdot d_{il}}{\sum_l d_{il}}$.

Handset prices: I create a monthly handset price index $p_t^{handset}$ based on 160 popular models in Rwanda, adjusting for quality and weighting each model by the quantity activated on the network.

Consumer survey: I fielded a small consumer survey in Rwanda in the summer of 2017, to determine how consumers select between mobile phone operators in a competitive market.

4. Model

In this section I develop a model of handset adoption and usage, adapted from Bjorkegren (2018) to allow for competition. Since the utility of owning a phone is derived from making calls, I begin in reverse, with a model of usage.

Consumers. Let $\bar{G}$ be the communication graph of Rwanda (a directed social network), with N nodes representing all individuals in the country. A directed link $ij \in \bar{G}$ indicates that i would have a potential desire to call j via phone. I assume that links are fixed. i's choice of operator affects the cost of placing calls, but operators are interconnected, so i can subscribers of either operator.

Let $S_t \subseteq N$ be the set of individuals with phones in month t. Since I observe only individuals who adopt phones with the incumbent by the end of my data T, I observe the set $S_T \subseteq N$. This omits the small number of individuals who subscribed to the incumbent's first competitor (less than 12% of the market); I assume that these individuals continue to use that operator in any counterfactual.[15] It also omits any other individuals who may have adopted if conditions were more favorable. I report simulation results for shorter time horizons $\tilde{T}$, during which results would not be affected by the behavior of these dark nodes (discussed further in the Simulation section). Since I only observe a link if a call was placed, I observe the subgraph, $G^T \subseteq \bar{G}$, where $ij \in G^T$ if i has called j by period T.[16] As shorthand, define $G_i = \left\{ j \,\middle|\, ij \in G^T \right\}$ as i's set of contacts.

Calling decision. In each period t that individual i has a phone, he can call any contact j that currently subscribes, $j \in G_i \cap S_t$. i draws a communication shock $\epsilon_{ijt} \overset{iid}{\sim} F_{ij}$ representing a desire to call j, and chooses a total duration $d_{ijt} \geq 0$ for that month, earning utility:

$$u_{ijt} = \max_{d_{ijt} \geq 0} \left[\frac{1}{\beta_{cost}} v_{ij}(d, \epsilon_{ijt}) - c_{ijt} d \right] \tag{1}$$

[15] Operator B used CDMA, a technology incompatible with the other GSM networks, and thus it would have been costly for individuals to switch. In my data I do not observe calls between Operators A and B.

[16] This will miss any links between subscribers where there is a latent desire to communicate but no call has been placed by T ($G^T \subseteq \bar{G}^T$). See Supplemental Appendix of Bjorkegren (2018).

where $v(d, \epsilon)$ represents the benefit of making calls of total duration of d, c_{ijt} represents the per-second cost, and β_{cost} corresponds to a coefficient on price (which converts between utils and money).

I model the benefit of making calls as:

$$v_{ij}(d, \epsilon) = d - \frac{1}{\epsilon}\left[\frac{d^{\gamma}}{\gamma} + \alpha d\right]$$

where the first term represents a linear benefit; $\gamma > 1$ controls how quickly marginal returns decline, and α controls the intercept of marginal utility, and thus the fraction of months for which no call is placed.[17]

In estimation and monopoly simulations, each individual i may only select the incumbent operator ($a_{it} = 0$); in counterfactuals, each individual i may select either the incumbent or an entrant ($a_{it} \in \{0, 1\}$). The choice of operator affects the marginal cost of placing a call:

$$c_{ijt} = p_t^{a_{it}a_{jt}} + \beta_{coverage}\phi_{it}^{a_{it}}\phi_{jt}^{a_{jt}}$$

where $p_t^{a_{it}a_{jt}}$ is the per-second calling price for a call from firm a_{it} to a_{jt} (including any tax). In order to bound equilibria, I will later assume the regulator does not allow firms to charge different prices for offnet calls, so that $p_t^{a_{it}a_{jt}} = p_t^{a_{it}}$ (discussed in the Simulation section). $\beta_{coverage}\phi_{it}^{a_{it}}\phi_{jt}^{a_{jt}}$ represents the hassle cost when the caller or receiver have imperfect coverage, which is heterogeneous between links. An individual's coverage $\phi_{it}^{a} \in [0, 1]$ is derived from the fraction of the area surrounding his most used locations receiving cellular coverage in month t under firm a's rollout plan.

The benefit of an additional second of duration across a link is decreasing, so i will call j until the marginal benefit equals the marginal cost, at duration:

$$d(\epsilon, \mathbf{p}_t, \phi_{it}, \phi_{jt}, \mathbf{a}) = \left[\epsilon\left(1 - \beta_{cost}(p_t^{a_{it}a_{jt}} - \beta_{coverage}\phi_{it}^{a_{it}}\phi_{jt}^{a_{jt}})\right) - \alpha\right]^{\frac{1}{\gamma-1}} \tag{2}$$

which increases with the desire to communicate (ϵ) and decreases with cost. $\mathbf{p}_t$ represents the vector of prices by firm, $\boldsymbol{\phi}_t$ represents the vector of coverage by individual and firm, and $\mathbf{a}$ represents firm choices for each individual. If the desire to communicate is not strong enough, i does not call: $d_{ijt} = 0$ when $\epsilon_{ijt} \leq \underline{\epsilon}_{ijt} := \frac{\alpha}{1-\beta_{cost}\left(p_t^{a_{it}a_{jt}} - \beta_{coverage}\phi_{it}^{a_{it}}\phi_{jt}^{a_{jt}}\right)}$.

[17] This functional form was chosen to satisfy 8 reasonable properties for the utility from telephone calls; see Bjorkegren (2018).

Then, calls from i to j in period t have expected duration:

$$Ed_{ij}(\mathbf{p}_t, \boldsymbol{\phi}_t, \mathbf{a}) = \int_{\underline{\epsilon}_{ijt}}^{\infty} d(\epsilon, \mathbf{p}_t, \boldsymbol{\phi}_t, \mathbf{a}) \cdot dF_{ij}(\epsilon)$$

and provide expected utility:

$$Eu_{ij}(\mathbf{p}_t, \boldsymbol{\phi}_t, \mathbf{a}) = \int_{\underline{\epsilon}_{ijt}}^{\infty} \left[d(\epsilon, \mathbf{p}_t, \boldsymbol{\phi}_t, \mathbf{a}) \cdot \left(\frac{1}{\beta_{cost}} \left(1 - \frac{\alpha}{\epsilon} \right) - p_t^{a_{it}a_{jt}} - \beta_{coverage} \phi_{it}^{a_{it}} \phi_{jt}^{a_{jt}} \right) - \frac{1}{\beta_{cost}\epsilon} \frac{d(\epsilon, p_t, \boldsymbol{\phi}_t, \mathbf{a})^{\gamma}}{\gamma} \right] dF_{ij}(\epsilon)$$

If they are valued, incoming calls provide utility:

$$E\tilde{u}_{ji}(\mathbf{p}_t, \boldsymbol{\phi}_t, \mathbf{a}) = \int_{\underline{\epsilon}_{jit}}^{\infty} \left[d(\epsilon, \mathbf{p}_t, \boldsymbol{\phi}_t, \mathbf{a}) \cdot \left(\frac{1}{\beta_{cost}} \left(1 - \frac{\alpha}{\epsilon} \right) - \beta_{coverage} \phi_{it}^{a_{it}} \phi_{jt}^{a_{jt}} \right) - \frac{1}{\beta_{cost}\epsilon} \frac{d(\epsilon, p_t, \boldsymbol{\phi}_t, \mathbf{a})^{\gamma}}{\gamma} \right] dF_{ji}(\epsilon)$$

Altogether, each month i uses network a_{it}, he receives actual expected utility from each contact who has also adopted:

(3)
$$Eu_{it}(\mathbf{p}_t, \boldsymbol{\phi}_t, \mathbf{a}, \boldsymbol{x}_{G_i}) = \sum_{j \in G_i \text{ and } x_j \leq t} [Eu_{ij}(\mathbf{p}_t, \boldsymbol{\phi}_t, \mathbf{a}) + w \cdot E\tilde{u}_{ji}(\mathbf{p}_t, \boldsymbol{\phi}_t, \mathbf{a})] - s \cdot 1_{\{a_{it} \neq a_{it-1}\}}$$

where x_j represents j's adoption time and $w \in [0, 1]$ specifies whether recipients value incoming calls. s represents the cost of switching operators.[18]

However, at the point of adoption, i anticipates that having a phone in month t will provide utility:

$$E\hat{u}_{it}(\mathbf{p}_t, \boldsymbol{\phi}_t, \mathbf{a}, \boldsymbol{x}_{G_i}) = Eu_{it}(\mathbf{p}_t, \boldsymbol{\phi}_t, \mathbf{a}, \boldsymbol{x}_{G_i}) + \eta_i^{a_{it}}(1 - \delta)$$

where an individual's type (η_i^0, η_i^1) represents heterogeneity in the anticipated utility of using a phone on each operator that is unobserved to the econometrician. Types need not be mean zero, but to make simulation tractable I do require that each individual's type is constant over time and across counterfactuals. Each month that i does not have a phone he receives utility zero.

Adoption decision. Conditional on the adoption decisions of others, an individual's adoption decision is an optimal stopping problem. At period t, i knows the current price of a handset, $p_t^{handset}$ (inclusive of any tax). He believes his contacts will adopt

[18]This would include the cost of changing accounts (swapping SIM cards and adjusting any settings), and notifying contacts about the change in phone number.

at times $\boldsymbol{x}_{G_i}$ using firms $\mathbf{a}_{G_i}$, and that in period $x > t$, the handset price will be $E_t p_x^{handset}$, a deterministic function that is described in the following section. He expects the utility of adopting at time x with operator sequence $\mathbf{a}_i$ to be:

$$(4) \qquad E_t U_i^{\mathbf{a}_i,x}(\mathbf{p}, \boldsymbol{\phi}, \boldsymbol{x}_{G_i}, \mathbf{a}_{G_i}) = \delta^x \left[\sum_{s \geq x}^{\infty} \delta^{s-x} E\hat{u}_{is}(\mathbf{p}_s, \boldsymbol{\phi}_s, \mathbf{a}, \boldsymbol{x}_{G_i}) - E_t p_x^{handset} \right]$$

i adopts in the first month x_i where he expects adopting immediately to be more attractive than waiting, given his beliefs about contacts' adoptions:

$$(5) \qquad \min\ x_i\ s.t. \left[\max_{\mathbf{a}_i} E_{x_i} U_i^{\mathbf{a}_i,x_i}(\mathbf{p}, \boldsymbol{\phi}, \boldsymbol{x}_{G_i}, \mathbf{a}_{G_i}) \geq \max_{s > x_i, \tilde{\mathbf{a}}_i} E_{x_i} U_i^{\tilde{\mathbf{a}}_i,s}(\mathbf{p}, \boldsymbol{\phi}, \boldsymbol{x}_{G_i}, \mathbf{a}_{G_i}) \right]$$

and selects operator sequence $\mathbf{a}_i$ to maximize utility.

Consumer surplus. The expected net present value of consumer surplus through $\tilde{T} \leq T$ is given by:

$$U_{net}^{\tilde{T}} = \sum_{i \in S_T \text{ and } x_i \leq \tilde{T}} \left[\sum_{t \geq x_i}^{\tilde{T}} \delta^t E u_{it}(\mathbf{p}_t, \boldsymbol{\phi}_t, \mathbf{a}, \boldsymbol{x}_{G_i}) - \left(\delta^{x_i} p_{x_i}^{handset} - \delta^{\tilde{T}} p_{\tilde{T}}^{handset} \right) \right]$$

which is net of calling, handset, and hassle costs. I compute handset costs assuming each handset is provided by a competitive market at marginal cost, and is sold back at the end of the data at the prevailing price.[19]

This will be an unbiased measure of the total consumer surplus of the network as long as any individuals not observed in my data $i \in N \backslash S_T$ would elect to delay adoption beyond $\tilde{T}$, given prices $\mathbf{p}$, coverage $\boldsymbol{\phi}$, and adoption $\mathbf{a}, \boldsymbol{x}_{G_i}$. I assess this in the Simulation section.

Firms. Each firm F commits to a path of calling prices $\mathbf{p}^F$ and a tower building plan $\mathbf{z}^F$ through horizon $\tilde{T}$ to maximize net present profits:

$$\pi_F^{\tilde{T}}(\mathbf{p}, \boldsymbol{z}, \mathbf{a}, \mathbf{x}, \boldsymbol{f}) = R_F^{\tilde{T}}(\mathbf{p}, \boldsymbol{z}, \mathbf{a}, \mathbf{x}, \boldsymbol{f}) - C_F^{\tilde{T}}(\mathbf{p}, \boldsymbol{z}, \mathbf{a}, \mathbf{x})$$

Firm F earns revenue from the calls of their own subscribers and from interconnection fees charged to the competitor's subscribers who call in to the network:

[19] I omit the type η_i^a that enters the individual's adoption decision, because this term may pick up forecast errors that do not represent the utility individuals receive.

$$R_F^{\tilde{T}}(\mathbf{p}, \boldsymbol{z}, \mathbf{a}, \mathbf{x}, \boldsymbol{f}) = \sum_{i \in S_T} \sum_{t \geq x_i}^{\tilde{T}} \delta^t \sum_{j \in G_i \cap S_t} Ed_{ij}(\mathbf{p}_t, \boldsymbol{\phi}_t(\mathbf{z}), \mathbf{a}) \cdot \Bigg[\overbrace{(1 - \tau_{it}^{usage}) p_t^{a_{it} a_{jt}} \cdot 1_{\{a_{it}=F\}}}^{\text{Subscribers}} + \underbrace{f_{ij} \left[1_{\{a_{it} \neq F \cap a_{jt} = F\}} - 1_{\{a_{it}=F \cap a_{jt} \neq F\}} \right]}_{\text{Interconnection}} \Bigg]$$

where $\boldsymbol{\phi}_t(\mathbf{z})$ is the coverage provided at time t under the rollout plans $\mathbf{z} = \{\mathbf{z}^0, \mathbf{z}^1\}$, τ_{it}^{usage} represents the airtime tax rate, and f_{ij} is the interconnection rate. The firm does not factor in that its actions affect the stock of subscribing consumers at $\tilde{T}+1$; results will be equivalent to a case where the firm expects consumers to have an opportunity to switch operators costlessly at $\tilde{T}+1$.

Firm F incurs costs:

$$\begin{aligned} C_F^{\tilde{T}}(\mathbf{p}, \boldsymbol{z}, \mathbf{a}, \mathbf{x}) \quad &= K_{rural} \cdot \sum_{z \in \mathbf{z}^F, z \text{ is off grid}} \sum_{t \geq x_z}^{\tilde{T}} \delta^t \\ &+ \sum_{i \in S_T} \sum_{t \geq x_i}^{\tilde{T}} \delta^t \sum_{j \in G_i \cap S_t} Ed_{ij}(\mathbf{p}_t, \boldsymbol{\phi}_t(\mathbf{z}), \mathbf{a}) \cdot (ic_{L_i, onnet_{ij}}^{out} \cdot 1_{\{a_{it}=F\}} + ic_{L_j, onnet_{ij}}^{in} 1_{\{a_{jt}=F\}}) \\ (6) \quad &+ \sum_{t \geq \min\{x_z | z \in \mathbf{z}^F\}}^{\tilde{T}} \delta^t \left(fc^F + lc^F \right) \end{aligned}$$

K_{rural} represents the annualized cost of owning and operating a rural tower.[20] $ic_{L_i, onnet_{ij}}^{Y}$ is the incremental cost of operating a network that sends or receives an additional second, including switching equipment, staff, central operations, and costs of capital. I allow the cost to vary by the direction of the call $Y \in \{\text{out}, \text{in}\}$, whether the two parties are on the same network, and whether each subscriber is primarily urban or rural $L_i \in \{\text{urban}, \text{rural}\}$. Each month that its network is operational, operator F also incurs fixed cost fc^F and license fee lc^F regardless of the size of its operations. I infer these costs from two cost studies commissioned by the regulator, described in the Estimation section.

[20] I define a tower as urban if it covers Kigali or one of Rwanda's 5 largest towns; a subscriber is defined as urban if his most used tower is urban.

Government. The government decides whether to grant a license to the entrant firm, and if so, sets the interconnection policy f_{ij} and license fee lc^F. The government also earns revenue from taxes on adoption ($\tau_{it}^{handset}$) and usage (τ_{it}^{usage}):

$$R_G^{\tilde{T}}(\mathbf{p}, \boldsymbol{z}, \mathbf{a}, \mathbf{x}) = \sum_{F \in \{0,1\}} \sum_{t \geq \min\{x_z | z \in \mathbf{z}^F\}}^{\tilde{T}} \delta^t lc^F + \sum_{i \in S_T \text{ and } x_i \leq \tilde{T}} \left[\delta^{x_i} \tau_{ix_i}^{handset} p_{x_i}^{handset} + \sum_{t \geq x_i}^{\tilde{T}} \left(\delta^t \tau_{it}^{usage} \sum_{j \in G_i \cap S_t} p_t^{a_{it} a_{jt}} \cdot Ed_{ij}(\mathbf{p}_t, \boldsymbol{\phi}_t, \mathbf{a}) \right) \right]$$

I do not take a stand on whether the government maximizes welfare, revenue, or another objective.

Equilibrium. An equilibrium reconciles firm choices with the network of consumer choices.

In Rwanda as in many countries, regulators require firms to submit a 5 year rollout plan as a condition for receiving or renewing a license.[21] To make simulation tractable, I assume the regulator requires firms to commit to a $\tilde{T}$ month plan (less than 5 years) that includes rollout as well as a path of prices, at the beginning of the license period.

At the beginning of time, the interconnection terms $\boldsymbol{f}$ are set, either by the incumbent (unregulated interconnection) or the government (regulated interconnection). There may be multiple consumer adoption equilibria; I exploit the game's approximately supermodular structure to study an approximately highest and approximately lowest equilibrium. Firms anticipate which equilibrium consumers will coordinate on and are aware of consumer types $\boldsymbol{\eta}$. Each firm simultaneously announces their price sequence $\mathbf{p}^F$ and tower construction plan $\mathbf{z}^F$, and each individual announces their adoption date x_i and operator sequence $\mathbf{a}_i$. More formally:

Given a vector of consumer types $\boldsymbol{\eta}$, interconnection terms $\boldsymbol{f}$, and horizon $\tilde{T}$, an **ε-equilibrium $\boldsymbol{\Gamma}(\boldsymbol{\eta}, \boldsymbol{f}, \tilde{T})$** is a tuple $(\mathbf{p}^0, \mathbf{p}^1, \mathbf{z}^0, \mathbf{z}^1, \mathbf{a}, \mathbf{x})$ such that:

- $(\mathbf{x}, \mathbf{a})$ is a network adoption partial equilibrium given $(\mathbf{p}^0, \mathbf{p}^1, \mathbf{z}^0, \mathbf{z}^1)$
- Each firm F cannot profit more than ε by deviating from price sequence $\mathbf{p}^F$ and tower construction plan $\mathbf{z}^F$ before $\tilde{T}$, given the competing firm's price

[21] These appear to be enforced: in 2007, Operator B was fined for failing to comply with its coverage and rollout plan. See Supplemental Appendix for requirements attached to the 2008 rollout plan.

sequence and tower construction plan, interconnection terms, and individual adoption dates and operator choices:

$$\pi_F^{\tilde{T}}(\mathbf{p}^F, \mathbf{p}^{-F}, \boldsymbol{z}^F, \boldsymbol{z}^{-F}, \mathbf{a}, \mathbf{x}, \boldsymbol{f}) \geq \pi_F^{\tilde{T}}(\mathbf{p}^{F*}, \mathbf{p}^{-F}, \boldsymbol{z}^{F*}, \boldsymbol{z}^{-F}, \mathbf{a}, \mathbf{x}, \boldsymbol{f}) - \varepsilon \text{ for all } \mathbf{p}^{F*} \text{ and } \mathbf{z}^{F*}$$

Given firm choices $(\mathbf{p}^0, \mathbf{p}^1, \mathbf{z}^0, \mathbf{z}^1)$ and a vector of consumer types $\boldsymbol{\eta}$, a **network adoption partial equilibrium** $(\mathbf{x}, \mathbf{a})$ is defined by adoption dates $\boldsymbol{x} = [x_i]_{i \in S_T}$ and operator choices $\mathbf{a} = [\mathbf{a}_i]_{i \in S_T}$ such that:

- Each initial adopter $i \in S_0$ selects operator sequence $\mathbf{a}_i \in \{0,1\}^{\bar{T}}$ optimally according to Equation 5, with beliefs consistent with his contacts' decisions
- Every other observed adopter $i \in S_T \backslash S_0$ selects adoption date $x_i \in \{1, ..., \bar{T}\}$ and operator sequence $\mathbf{a}_i \in \{0,1\}^{\bar{T}-x_i}$ optimally according to Equation 5, with beliefs consistent with his contacts' decisions

Expectations. Individuals correctly forecast call prices p_x, coverage $\boldsymbol{\phi}_x$, the dates their contacts adopt $\boldsymbol{x}_{G_i}$, and their contacts' operator choices $\mathbf{a}_{G_i}$. Because a handset becomes sunk at the time of purchase, forecasts of future prices can sway the adoption decision. I assume that at each period t, individuals learn the current handset price and expect the price in future periods to decline at an exponential rate consistent with the overall decline over this period:

$$E_t p_x^{handset} = \omega^{x-t} p_t^{handset}$$

for $\omega = \left(\frac{p_{\bar{T}}^{handset}}{p_0^{handset}}\right)^{\frac{1}{\bar{T}}}$.

Together, this notion corresponds to an equilibrium of a game where each individual adopts at the first sufficiently attractive date, based on the expected path of handset prices, and the actual decisions of contacts. It implies that individuals do not anticipate how later adopters will respond to their actions, because later adopters may not condition their strategy on actions in prior periods.[22] It also introduces a slight inconsistency: when i decides whether to adopt in period x_i, he does not know future handset prices, but does know the adoption dates of his future contacts, whose decisions will have incorporated future handset prices. I tolerate this inconsistency in order to have a computable notion of equilibrium.

[22]This results in an open loop equilibrium; see for example Fudenberg and Levine (1988).

If at the point of adoption, an individual forecasts differently than specified here, the error will be captured in his type (η_i^0, η_i^1), as long as the error is fixed across time and counterfactuals.[23]

This notion allows for rich behavior: a perturbation of utility that causes one individual to change their adoption date can shift the equilibrium, inducing ripple effects through potentially the entire network. Firms internalize revenue from network effects in their own networks, but not from network effects that spill over into competing networks (except to the extent that these are partially recovered through interconnection fees).

Under this definition, there are likely to be multiple adoption equilibria. However, the adoption game is approximately supermodular; I use the resulting approximate lattice structure to bound equilibria.

5. Estimation

Consumer decisions when there is a single operator. In the observed monopoly environment, individuals choose when to adopt a mobile phone and, if they adopt, how to use the phone. The usage decision reveals the value of each connection, and how that value changes with prices and coverage. The adoption decision reveals any residual factors affecting adoption with the incumbent (individual type η_i^0). I use the primitives estimated in Bjorkegren (2018).

Identification. Traditional approaches towards network goods estimate the value of each connection indirectly, based on correlations in adoption. For example, consider individual i who has one link, does not consider the future ($\delta = 0$), and is deciding whether to adopt, $A_i \in \{0, 1\}$. i will adopt if the value exceeds the cost:

$$A_i = I\left(\theta_{ij} A_j + \eta_i^0 \geq p_t^{handset}\right)$$

where θ_{ij} is the value of the link if j also adopts. It is difficult to estimate θ_{ij} from correlations in adoption: each individual's adoption depends on the other's, as well as any unobserved shocks, which are likely to be correlated (Manski, 1993). Approaches

[23]To assess the importance of forward looking behavior, Bjorkegren (2018) also estimates and simulates results under a myopic model where individuals do not consider the future in their adoption decision, for the monopoly case.

that instrument for adoption tend to rely on very particular variation, and yield crude measures of value.[24]

Rather than inferring θ_{ij} from correlated adoption, I measure it directly. A link provides value because it enables calls:

$$\theta_{ij} = Eu_{ij}(p_t^0, \boldsymbol{\phi}_t^0)$$

I identify a link's value by how its usage changes in response to changes in the cost of communicating. The value of all links together represent the value of the network.

My approach requires that the latent desire to communicate (ϵ_{ijt}) is uncorrelated with costs (p_t^0 and $\phi_{it}^0\phi_{jt}^0$, which both improve over time). As the network grows, the composition of subscribers changes, and the operator may adjust prices and coverage in response. I absorb compositional changes by using only within-link variation to estimate the response of usage to costs. My identification assumption implies that the value of communicating with a particular contact does not otherwise trend over time, or depend on who else has adopted. I test this assumption by analyzing changes in calling patterns across links; results are consistent with these factors being negligible.[25] Apart from these restrictions, communication shocks can be arbitrarily correlated between any links in the network.

After the network portion of utility (θ_{ij}) is estimated, it is straightforward to back out any residual heterogeneity affecting adoption, η_i^0. These types may be arbitrarily correlated between nodes, but are fixed over time and across counterfactuals.

Call decision. Call decisions reveal the country's latent communication graph (the call shock distributions F_{ij}), the shape of the utility function (γ and α), and how usage responds to cost (β_{cost} and $\beta_{coverage}$). I allow the call shock distributions to vary at the link level $\epsilon_{ijt} \overset{iid}{\sim} F(\sigma_i, q_i, \mu_{ij})$ (an analogue of link fixed effects), so that the response of usage to cost is identified within-link (how does usage across a given

[24]For example, Tucker (2008) identifies the value of a videoconferencing system using variation in television watching partly driven by the World Cup. Instrumental variable approaches do not capture rich heterogeneity, or account for how the cost of using a link affects its value.

[25]I evaluate whether the duration of calls across a link changes with the time since an individual adopted, or as more of the sender's and receiver's contacts join the network, after controlling for cost. For the median subscriber, the change in duration associated with either the change in time and contacts on the network is less than 5% of the change associated with the changes in prices and coverage over this time period. See Supplemental Appendix.

link change as prices and coverage change). I specify the distribution for call shocks $\epsilon_{ijt} \overset{iid}{\sim} F_{ij}$ as a mixture distribution:

$$F_{ij}\left[\epsilon\right] = q_i \Phi\left(\frac{\ln\left(\epsilon\right) - \mu_{ij}}{\sigma_i}\right) + (1 - q_i) 1_{\{\epsilon > -\infty\}}$$

where $\Phi(\cdot)$ represents the standard normal CDF. The first component is a log-normal distribution, $\ln N(\mu_{ij}, \sigma_i^2)$, which captures a continuous spread of potential communication. It suggests that an individual will not call across a link if the shock is too low relative to the cost (affected by α in the utility function). However, on a given link, a large fraction of months have no calls. To better explain these I also include a point mass, under which there are no calls regardless of the cost (controlled by the individual parameter q_i).

In each period t, for each link between subscribers, I observe a duration $d_{ijt} \geq 0$. Equation 2 recovers the underlying call shock ϵ:

$$\epsilon\left(d, p_t, \phi_{it}, \phi_{jt}\right) = \frac{d^{\gamma - 1} + \alpha}{1 - \beta_{cost}\left(p_t + \beta_{coverage}\phi_{it}\phi_{jt}\right)}$$

given coverage under the baseline rollout plan $\boldsymbol{\phi}_t(\mathbf{z}_0)$. If the call shock was not high enough to place a call of at least one second, the month will have no call ($d_{ijt} = 0$), with likelihood $F_{ij}\left[\epsilon\left(1 \text{ second}, \ldots\right)\right]$. The likelihood of calls of total duration d_{ijt} is $F_{ij}\left[\epsilon\left(d_{ijt} + 1, \ldots\right)\right] - F_{ij}\left[\epsilon\left(d_{ijt}, \ldots\right)\right]$.

These are combined into the log-likelihood function:

(7)

$$\begin{aligned}\ln L(\Theta) = \sum_i \sum_t \sum_{j \in S_t \cap G_i} \quad & 1_{\{\text{call placed}_{ijt}\}} \ln\left(F_{ij}\left[\epsilon\left(d_{ijt} + 1, p_t, \phi_{it}, \phi_{jt}\right)\right] - F_{ij}\left[\epsilon\left(d_{ijt}, p_t, \phi_{it}, \phi_{jt}\right)\right]\right) \\ & + \left[1 - 1_{\{\text{call placed}_{ijt}\}}\right] \ln F_{ij}\left[\epsilon\left(1 \text{ second}, p_t, \phi_{it}, \phi_{jt}\right)\right]\end{aligned}$$

The full sample has 1,525,061 nodes, 414.5 million links, and a total of 15 billion link-month duration observations. The calling decision has 7 types of parameters. I assume that the shape and sensitivity parameters are common to all links (γ, α, β_{cost}, $\beta_{coverage}$). I allow the parameter scaling the shock distribution (σ_i), and the probability of no call at any price ($1 - q_i$) to vary at the individual level. I allow the shock distribution to be shifted at the link level, with structure:

$$\mu_{ij} = \mu_i + \mu_{\max(x_i, x_j), \overline{\phi_{it}\phi_{jt}}}$$

which includes an individual mean term μ_i, and a cost fixed effect for each combination of link adoption date ($\max\{x_i, x_j\}$) and average coverage ($\overline{\phi_{it}\phi_{jt}}$), discretized to 519 combinations. This term ensures that price and coverage sensitivity are identified off of within-link changes in calling.[26]

I estimate these parameters in two steps. First, I jointly estimate the common parameters, cost fixed effects, and distribution parameters for a random 0.5% subset of nodes and their full set of links.[27] Then, I impose the common parameters and cost fixed effects to estimate the remaining distribution parameters (q_i, σ_i, μ_i; 4.6 million altogether). Conditional on the common parameters and cost fixed effects, an individual's distribution parameters affect only his own likelihood, so this last step is computationally much less demanding than performing a full joint estimation.

Adoption decision. The adoption decision bounds an individual's type under the incumbent, η_i^0. Consider the utility i would have received had he adopted a different month. At time x_i, i bought a handset rather than waiting K months. Holding fixed the actions of others, Equation 5 implies $E_{x_i}U_i^{0,x_i}(\boldsymbol{x}_{G_i}, \mathbf{0}) \geq E_{x_i}U_i^{0,x_i+K}(\boldsymbol{x}_{G_i}, \mathbf{0})$. This implies that the expected utility of being on the network during the following K months must have exceeded the expected drop in handset prices:[28]

$$\sum_{s=0}^{K-1} \delta^s E u_{ix_i+s}(p_{x_i+s}, \boldsymbol{\phi}_{x_i+s}, \boldsymbol{x}_{G_i}, \mathbf{0}) + (1-\delta^K)\eta_i^0 \geq p_{x_i}^{handset} - \delta^K E_{x_i} p_{x_i+K}^{handset} \tag{8}$$

Similarly, i could have purchased a handset earlier. At time $x_i - K$, i chose to wait, so he must have preferred some future adoption date: for some $\tilde{K} > 0$, $E_{x_i-K}U_i^{0,x_i-K+\tilde{K}}(\boldsymbol{x}_{G_i}, \mathbf{0}) \geq$

[26]To see how this formulation addresses the selection issue, note that the numerator inside the standard normal CDF in $F_{ij}[\epsilon(d)]$ can be written: $\ln\left(d^{\gamma-1}+\alpha\right) - \ln\left(1-\beta_{cost}\left(p_t + \beta_{coverage}\phi_{it}\phi_{jt}\right)\right) - \mu_{ij}$. Consider the decomposition $\mu_{ij} = \mu_i + e_{ij}$ where μ_{ij} is the true link mean and e_{ij} is an error. If the estimated specification only includes μ_i, and if e_{ij} is correlated with p_t or $\phi_{it}\phi_{jt}$, then estimates of β_{cost} and $\beta_{coverage}$ may be biased. While each link faces the same price series over time, links that join the network later face lower prices on average: the price path faced by a link is summarized by the link's adoption date. Each link faces a different coverage path; I approximate these with the average joint coverage using 10 bins.

[27]The approximately 0.5% sample is 8,000 nodes with 1,317,539 links and 39 million link-month observations (2.6 million with calls).

[28]The model implies that i correctly forecasts the first K months of utility and his expectation of the continuation flow does not change between x_i and $x_i + K$. Both options provide the same continuation flow of utility after $x_i + K$, so they differ only in the utility provided in the first K months.

$E_{x_i-K}U_i^{0,x_i-K}(\boldsymbol{x}_{G_i},\mathbf{0})$. He must have valued those $\tilde{K}$ months of expected utility less than the expected drop in handset prices:

(9)
$$\sum_{s=0}^{\tilde{K}-1}\delta^s Eu_{i,x_i-K+s}(p_{x_i-K+s},\boldsymbol{\phi}_{x_i-K+s},\boldsymbol{x}_{G_i},\mathbf{0})+(1-\delta^{\tilde{K}})\eta_i^0 \leq p_{x_i-K}^{handset}-\delta^{\tilde{K}}E_{x_i-K}p_{x_i-K+\tilde{K}}^{handset}$$

These inequalities imply bounds for each individual's type under the incumbent: $\underline{\eta}_i^0 \leq \eta_i^0 \leq \bar{\eta}_i^0$, where:

(10)
$$\underline{\eta}_i^0 = \frac{1}{1-\delta^K}\left[p_{x_i}^{handset}-\delta^K E_{x_i}p_{x_i+K}^{handset}-\sum_{s=0}^{K-1}\delta^s Eu_{i,x_i+s}(p_{x_i+s},\boldsymbol{\phi}_{x_i+s},\boldsymbol{x}_{Gi},\mathbf{0}) \right]$$
$$\bar{\eta}_i^0 = \max_{\tilde{K}>0}\left[\frac{1}{1-\delta^{\tilde{K}}}\left[p_{x_i-K}^{handset}-\delta^{\tilde{K}}E_{x_i-K}p_{x_i-K+\tilde{K}}^{handset}-\sum_{s=0}^{\tilde{K}-1}\delta^s Eu_{i,x_i-K+s}(p_{x_i-K+s},\boldsymbol{\phi}_{x_i-K+s},\boldsymbol{x}_{Gi},\mathbf{0}) \right]\right]$$

I set $K=2$ months.[29] Note that the future after $x_i+\max(K,\tilde{K}-K)$ cancels out of these expressions: as long as the next preferred adoption date occurs within the data, results are not sensitive to the evolution of the network beyond that point. These conditions are necessary for equilibrium and are valid in the presence of multiple equilibria. During months that extra fees were charged, I incorporate the fee schedule.[30] I set the discount factor to the inverse of the average real interest rate in Rwanda over this period: $\delta=(\frac{1}{1.07})^{1/12}\sim 0.9945$ (source: World Bank). I am able to recover η_i^0's for 0.8m nodes adopting between $x_i\in[K,T-K]$.[31]

Validation. As a robustness check, Bjorkegren (2018) tests whether the value implied by calls corresponds with the value implied by adoption. I form Equations 8 and 9

[29] I select K to balance two forces: lower values produce tighter bounds; higher ones smooth any shocks around their adoption date that are unaccounted for.

[30] Before June 2007, subscribers needed to add roughly \$4.53 in credit per month to keep their account open; I factor this in as a hassle cost. Actually opening an account entails purchasing a SIM card, which cost roughly \$1 itself plus the cost of an initial top up. See Supplemental Appendix of Bjorkegren (2018).

[31] I do not back out bounds for those receiving a rural handset subsidy in 2008 (for whom it is difficult to value the purchase), and whose activation does not coincide with the adoption of a new handset (altogether these account for 5% of last period durations). In simulations, I compute changes in the call model for all nodes, and hold the adoption of these fixed; doing so will tend to attenuate the results of policy counterfactuals.

into moment inequalities, using instrumental variables that shift adoption based on the cost of providing coverage to different areas due to Rwanda's hilly geography, in a manner similar to Yanagizawa-Drott (2014), as well as in the fraction of contacts who join in response to a government adoption subsidy program. Results suggest these valuations of calls and adoption are consistent under $w = 0$ (consumers value one dollar of call utility between \$1.02-1.17 of handset price), but under $w = 1$, the utility of calls is double counted. I proceed with $w = 0$ as the base specification.[32]

Consumer decisions with multiple operators. Parameters estimated under monopoly provision reveal how individuals trade off access to links, prices, and coverage. To estimate the costs of switching, and idiosyncratic preferences for the entrant, I posed hypothetical questions in a survey of mobile phone owners in Rwanda (see Appendix B.2). While choices in hypothetical scenarios do not always reveal true preferences, they can be effective predictors of behavior (Bernheim et al., 2013).

Consumers find it a hassle to switch operators, especially when a switch entails changing phone numbers. Based on an incremental switching exercise, I estimate a switching cost of $s = \$36.09$, corresponding to 6.8 months of household average airtime spending in 2010 (EICV). The switching cost drops to \$18.51 if consumers can keep their phone numbers when changing operators, which I consider as a counterfactual policy. To assess the quality of hypothetical responses, I ask respondents to make an additional hypothetical choice that is analogous to a choice observed within my data. I estimate the cost of switching between plans on the same operator, and find that estimates derived from data and hypothetical respnses do not differ significantly at the 1% level (see Appendix B.3).

I also construct an incremental switching exercise to isolate idiosyncratic operator preferences, holding prices and coverage constant. Consumers have a very slight idiosyncratic preference for the incumbent: the mean difference is $m(\eta_i^0 - \eta_i^1) = \$2.45$ (\$0.01 per month), and standard deviation $\sigma(\eta_i^1 - \eta_i^0) = \$6.72$. These preferences are not correlated with observables, and when asked to explain their choices, the most common response was a preference for one operator's branding or color scheme. In

[32]Bjorkegren (2018) finds that results do not differ substantially for several monopoly counterfactuals under the assumption $w = 1$; I do not test this in this paper because it would double very long computation times.

counterfactual simulations, I treat these differential preferences as random parameters: for each individual I draw $e_i \overset{iid}{\sim} N\left[m(\eta_i^0 - \eta_i^1), \sigma(\eta_i^1 - \eta_i^0)\right]$, and compute his type under the entrant $[\underline{\eta}_i^1, \bar{\eta}_i^1] = [\underline{\eta}_i^0 - e_i, \bar{\eta}_i^0 - e_i]$. To reduce the computational burden, I present results drawn from a single random seed; in a robustness test in the Supplemental Appendix, I find that the random draw has little effect on outcomes.

Firm costs. I infer firm costs from two studies commissioned by the Rwandan regulator.

I infer incremental costs $ic^Y_{L_i,onnet_{ij}}$ and fixed costs fc^F from PwC (2011), a confidential cost study commissioned to set interconnection rates.[33] This study constructs a detailed engineering breakdown of the network, using cost estimates obtained from operators and crosschecked against international benchmarks. It combines the costs of towers, switching equipment, staff, central operations, and capital to compute the Long Run Incremental Cost (LRIC) of sending or receiving an additional second of voice calls. I break down these costs to better match my setup, in three ways. First, the study inflates the incremental cost estimates with a proportional markup to cover fixed costs of operating the network; I report these fixed costs separately. The incumbent's fixed cost is constant across counterfactuals so is not relevant for results; I infer the entrant's fixed cost by multiplying the total incremental cost estimate by the same proportional markup used in the study. Second, I separate out the license fee paid to the regulator, lc^F. Third, I separate out the cost of rural tower investments. In urban areas, towers tend to be capacity constrained so that the number of towers scales with call volumes. However, in rural areas, remote towers tend not to be capacity constrained; they scale instead with coverage. For subscribers who primarily use urban towers ($L_i = urban$), I compute incremental costs including the cost of towers. For subscribers who primarily use rural towers ($L_i = rural$), I omit the incremental cost of towers and compute these separately as follows.

I infer the cost of building and operating a rural tower, K_{rural}, from RURA (2011), a public study commissioned to set the regulated prices of infrastructure sharing.[34] It

[33] Because this study is confidential, I am unable to report the cost estimates.

[34] I define a tower as urban if it covers Kigali or one of Rwanda's 5 largest towns; a subscriber is defined as urban if his most used tower is urban.

uses financial data provided by the operators to infer the annualized cost of owning and operating a rural tower.[35]

See Appendix B.1 for more details.

6. Simulation

Assumptions. I impose several restrictions to make simulation tractable. These restrictions are feasible competition rules that could be imposed by the regulator, so that my results will represent a lower bound on the benefits that could be obtained under more general competition rules.

Operators cannot charge different prices for on- and off-net calls ($p_t^{F,G} \equiv p_t^{F,G'}$). If alternately, both firms offered low on-net charges and high off-net charges, the number of equilibria proliferates: there may be one equilibrium where all consumers subscribe to the entrant, and another where all subscribe to the incumbent. Under those conditions, I do not have enough information to discipline the selection of equilibrium. While a rule to restrict off-net prices was not common in African markets at this time, it has been proposed for Rwanda (Argent and Pogorelsky, 2011), and has been used in several countries in an attempt to discipline competition (including Kenya, Singapore, Colombia, Turkey, Slovenia, and Portugal; see TMG (2011)).

No multihoming. In markets where different operators have low on-net prices and high off-net prices, it can be common for consumers to hold accounts with multiple operators to connect with others on different networks. Given that I restrict off-network pricing, there is less reason for consumers to hold multiple accounts. For simplicity I rule out that possibility.[36]

[35]Building a tower costs approximately $130,000; I consider the total cost of ownership to operate a tower, which includes operating expenses, annualized depreciation, and a 15% cost of capital. Calculated depreciation assumes lifespans of 15 years for towers, 8 years for electric grid access, and 4 years for generators. This results in a total annualized cost of owning and operating a tower in Rwanda of $51,000 per year, plus $29,584 for towers that are far from the electric grid that must be powered by generators.

[36]There could still be some reason: an individual who travels between an urban center and rural areas may want to hold a low price account that only has urban coverage as well as a higher price account that has better rural coverage.

Firm strategy space. I allow firms to set price paths as a multiple of the initial monopolist price path: $\mathbf{p}^F \in \psi \cdot \mathbf{p}^{monopoly}$, where ψ is chosen from a grid.[37]

During the period I study, the government imposed coverage requirements on the incumbent; Bjorkegren (2018) finds that these requirements resulted in the building of roughly 11% of the rural towers active by 2009. Had investment been less profitable, this requirement could have ceased to be viable. My main simulations hold fixed the incumbent's rollout plan and set the entrant's rollout plan to mimic the incumbent's rollout in urban areas but not cover rural areas (these plans correspond to the coverage maps in Figure 3).[38] I then compute the incumbent's incentives to adjust its investments in response to entry. In the Supplemental Appendix I also consider the equilibria in prices and coverage that would result if the coverage requirement were lifted.

Simulation algorithm. I simulate equilibria $\mathbf{\Gamma}(\boldsymbol{\eta}, \boldsymbol{f}, \tilde{T})$ in two nested steps.

Firm choices. I assume that firms know the communication graph, and consumers' types (η_i^0, η_i^1) up to the estimate I measure (which is either an upper or lower bound), and anticipate whether consumers will coordinate on a high or low network adoption partial equilibrium.

I consider a grid of potential regulator and firm choices (interconnection terms, and price and rollout paths: $\{(\boldsymbol{f}, \mathbf{p}^0, \mathbf{p}^1, \mathbf{z}^0, \mathbf{z}^1 | \boldsymbol{\eta}^0, \boldsymbol{\eta}^1)\}$). I identify an ε-equilibrium on this grid by allowing each firm to iteratively best respond to each other's strategy: conditioning on the decision of $-F$, firm F selects $\mathbf{p}^F$ and $\mathbf{z}^F$ to maximize profits

[37]Note that this implies that firm pricing does not diverge increasingly over time. The flow utility provided by a phone changes over time: it increases when others adopt, as calling prices decline, and as coverage improves. As a result, even if a consumer adopts before the end period T, his decision of which operator to select may depend on flow utility after T. When there are switching costs, he may select an operator that offers low flow utility before T because it provides higher flow utility after T. Since I am most confident about results before T, I restrict the impact of these continuation values. I also assume that during the early period when the incumbent charged extra fees, those are matched by the entrant. When competition was eventually introduced, operator prices appear to converge over time rather than diverge (see Figure 2 and Appendix Table A6).

[38]Operator C's global Annual Report in 2010 suggests an urban focus: 'There is scope for further coverage growth in our African markets, but urban centers currently represent the significant majority of the addressable population and we believe that the right approach to reaching more rural areas is increasingly to share network infrastructure with other operators.' Tower sharing in Rwanda was limited until it was mandated by the regulator in 2011.

through $\tilde{T}$, anticipating how consumers will adopt and use phones. This grid approximates a continuous surface; to limit computation burden, I first find an equilibrium on a coarse grid, and then iteratively refine the grid near that equilibrium.[39] Best responses can sometimes cycle locally around a small neighborhood; I terminate the algorithm once neither firm would earn more than $\varepsilon = \$2m$ by deviating. If the algorithm discovers multiple ε-equilibria, I report the one for which any profitable deviation is smallest. (See Appendix C for the implementation of the algorithm.)

Consumer choices. Conditional on firm and government choices, I simulate a network adoption partial equilibrium $(\mathbf{x}, \mathbf{a})$ using a two step iterated best response method, by exploiting the lattice structure of the set of adoption equilibria. i's optimal adoption date x_i is weakly monotonic in his type $\boldsymbol{\eta}_i$, and his contact's adoption date x_j, and coverage $\phi_j^{a_j}$.[40] In the monopoly case, or when one firm is weakly better for all consumers, equilibria can be bounded simply.[41] The lower bound of the equilibrium with lowest possible adoption, $\underline{\Gamma}$, can be identified by setting each individual's type $\boldsymbol{\eta}_i$ to its lower bound, and initializing the best response algorithm with a complete delay of adoption ($x_i^0 = \bar{T}$) with the operator with worst coverage. The upper bound of the highest possible equilibrium, $\bar{\Gamma}$, can be identified by setting each individual's type to its upper bound, and initial choice to adopt immediately ($x_i^0 = 0$) with the operator with best coverage.

However, when firms are differentiated in two dimensions, the lattice structure can bend. j's choice of operator affects both his adoption date (x_j) and coverage ($\phi_j^{a_j}$), which can have diverging effects on the rest of the network. An individual who switches to a lower priced operator may adopt earlier but have worse coverage, on balance this may make the network more desirable for some contacts and less desirable for others. I compute approximate bounds with a two step method. First, I compute the *quasi*equilibrium that would result from combining the best (worst) envelope of

[39] Because I trace out a large set of conditions $\boldsymbol{f}$ and $\tilde{T}$ that induce equilibria in different parts of the grid, I end up evaluating most of the grid finely (see normal form game boards in Appendix and Supplemental Appendix).

[40] A higher type η_i^a weakly decreases i's optimal adoption date, and a decrease in i's adoption date x_i or coverage $\phi_i^{a_i}$ weakly decreases j's optimal adoption date. This follows from the lattice structure of $\boldsymbol{x}$ and because $U^{x_i}(\eta_i, \boldsymbol{x}_{-i}, \boldsymbol{\phi}_i)$ has increasing differences in x_i and x_j, or is supermodular in $\boldsymbol{x}$; see Topkis (1978) and Milgrom and Shannon (1994).

[41] As in Bjorkegren (2018); see pseudocode in Appendix Section C.

coverage and prices offered by the two firms, which is monotonic and represents an upper (lower) bound.[42] Second, I start from that quasiequilibrium to compute the adoption equilibrium in the actual prices and coverage. To ease computation, I allow individuals to switch operators at most once.

On occasion, there remain slight nonmonotonicities which result in a cycle; if a cycle is small, I end the algorithm and consider the result an approximate equilibrium.[43] In a bounding exercise in the Supplemental Appendix, I find that the impact of these nonmonotonicities is small relative to the impact of the policies I study.[44]

Computing a single partial equilibrium takes about 15 hours on a supercomputer, so that computing the roughly 1,000 partial equilibria used in this paper takes approximately 625 supercomputer days.[45]

Dark network. If part of the dark network would have become activated prior to $\tilde{T}$, the above will underestimate demand. I thus evaluate whether equilibrium prices and coverage would induce the dark network to become active before $\tilde{T}$.

A node that adopted after T at baseline will adopt prior to $\tilde{T}$ in a counterfactual only if the network provides more value before $\tilde{T}$ than it did at baseline at T, based on the adoption condition in Equation 5. Thus a conservative bound can be obtained by setting $\tilde{T}^{conservative}(\mathbf{p}, \boldsymbol{\phi})$ so that each of calling prices, handset prices, coverage, and adoption lie within the conditions observed in sample. However, this bound neglects the relationship between these elements: in particular, in early months, handset prices remain a barrier to adoption for most of the network even if competition lowers usage prices. I exploit this relationship by using data from a later survey, and modeling the adoption decision of individuals in the dark network to construct $\tilde{T}^{approx}(\mathbf{p}, \boldsymbol{\phi})$. Details are described in Appendix D. These form my main results. In the Supplemental Appendix I also report results for $\tilde{T}^{conservative}(\mathbf{p}, \boldsymbol{\phi})$ and $\tilde{T}^{naive} = T$.

[42]Where call affordability is the inverse of pricing.

[43]If fewer than 40 nodes are shifted for at least 10 iterations.

[44]My approximate equilibria are bounded by the lattice of equilibria that result when consumers have naïve beliefs about their contacts' coverage (everyone believes that others have the coverage of the incumbent, or the entrant).

[45]To improve computational performance, I reoptimize nodes in parallel, with a synchronized record of all consumers' current choices. A given node is reoptimized only if its conditions or neighbors have changed (analogous to a breadth first search). I use secure computation nodes each with 340GB of RAM and 20 processors, housed at Brown University.

7. Monopoly Benchmarks

Before simulating a competitive equilibrium, I demonstrate how a monopoly model can diagnose how competition may affect the network. I trace the impact of prices on welfare, and how the revenue from building rural towers is distributed across the network. These diagnostics can be computed imposing fewer assumptions about an eventual competitor. I hold fixed individuals' operator choices ($a_{it} \equiv 0$), and simulate adoption under different conditions. Results are shown in Table 3. In this section, for simplicity I report results under the full period of the data: 2005-mid 2009 (ending at $\tilde{T}^{naive} = T$). This will result in correct estimates of incentives to invest but tend to underestimate the welfare benefits of lowering prices, since part of the dark network would have adopted earlier. At baseline during this period, the incumbent's mobile phone system provides net social welfare of \$411-\$461m, an amount equivalent to 2-3% of Rwandan GDP over the same period.

Lowering prices has large welfare benefits. Anticipating that competition may induce the incumbent to lower prices, I simulate the equilibria that would result if the monopoly were to charge the price that was eventually charged after Operator C entered in 2010 (see Figure 2). This amounts to an immediate drop in calling prices of 77%. I assume the firm holds this nominal price constant, and expands coverage as in the baseline. I compute first the proximal effect: allowing subscribers to individually reoptimize their usage and adoption holding fixed the adoption of others; and then any additional network effects as the impact of these decisions ripple through the network. This price reduction would have lowered firm and government revenues, and due also to the cost of operating a larger network, substantially reduced firm profits. However, it would have generated huge utility benefits, more than doubling the surplus accruing to consumers. On net, social welfare would have increased by \$218m (low equilibrium) or \$241m (high), which corresponds with 1% of GDP or 7-8% of official development aid over this time period. Most of the welfare improvement comes from proximal effects; 9-15% comes from network ripple effects.

Investment in rural towers generates network spillovers. Investing in one portion of a network can generate network effects that spill over into other portions.

When a network is operated by a single firm, that firm may be able to internalize those spillovers. However, when a network is split by competition, the benefits of an investment may spill over into a competing network (if the networks are interconnected), or be partly foregone (if the networks are not connected). As a result, competition can lower incentives to invest, depending on how the network is split, and how benefits from a given investment ripple through the network.

I estimate the scope for competition to affect investment by decomposing the revenue generated under monopoly provision by region. Urban areas tend to be more lucrative (population densities are high and operating costs are lower) and thus profitable to serve even in the presence of competition. However, serving a rural area may be profitable only if one also has a monopoly over urban areas. If market share in urban areas is split between competitors, an operator may invest less in rural coverage: it will internalize less of the spillover benefits of investment, and if it is not allowed to charge different prices to rural and urban areas, price pressure in the urban area may limit its ability to recoup its investment.

I simulate the effects of building full baseline coverage relative to a counterfactual where only urban towers were built (see Figure 3 for coverage maps). I impose the relevant coverage map, allow each consumer to adjust their adoption and calling behavior, and compute resulting equilibrium revenues and utility. I compute first the proximal effect:, and then any additional network ripple effects.

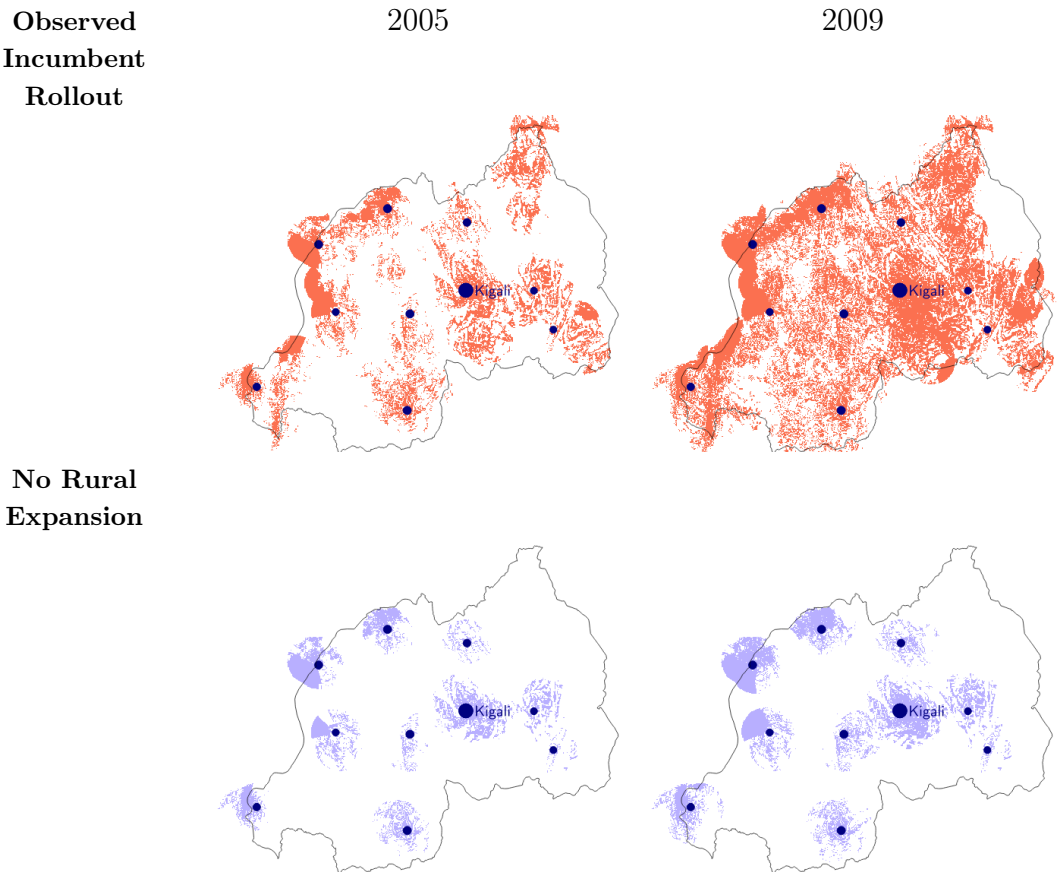
First, I simulate the impact of removing rural expansion, holding prices fixed at the monopoly level. As shown in Table 3, while only rural areas received improved coverage, 31% (29%) of revenue came from links between rural and urban areas, and 44% (48%) came from urban-urban links. If the network were split, the incumbent would internalize only a fraction of these components of revenue.

Revenue from connections between urban and rural networks may be partly internalized through interconnection charges.

Urban-urban revenue can be further decomposed into two parts:

A proximal effect: some urban consumers make calls from rural areas and thus directly benefit from rural coverage (which would be factored into their coverage measure ϕ^a_{it}). This accounts for most of the increased urban-urban revenue (92% or

FIGURE 3. Rollout Plans



75%). These urban consumers value both price and rural coverage, so if they were faced with an additional urban competitor, they would select an operator based on both prices and coverage, creating an incentive for operators to increase the quality of coverage.

Spillover benefits that ripple into the large urban network, which affect even consumers who have no desire to call or use rural coverage. This accounts for the remainder of revenue (8% or 25%). Because this latter portion comes from the interior of the urban network, if the network were split, standard interconnection charges at the boundary of the networks would not help the incumbent internalize this revenue. Competition can thus lower these incentives to invest.

While the rural expansion was profitable at monopoly prices, if prices are reduced to the eventual competitive price, incentives to build out the rural network are substantially lower (and negative), as shown in the final row of Table 3.

These simulations suggest that competition has the potential for large welfare impacts but may impact investment. The next section discusses assumptions needed to simulate competition. Section 9 presents results under competition.

8. Extension to Competition

This section evaluates how sufficiently the model estimated in a contested monopoly environment captures behavior under competition. The model imposes constraints on how operators would compete, and how consumers would respond. In particular, I require that the individual types for the incumbent η_i^0, and the latent call graph (μ_{ij}, σ_i, q_i) are stable upon the introduction of competition.

To evaluate these assumptions I use two kinds of evidence. First, I use my original consumer choice survey, other surveys, and official statistics from Rwanda, after a viable competitor entered the market (after 2009). Second, I report evidence from other African countries that had competitive markets during this time.

What margins might operators compete on? The model captures competition on coverage and price levels (which may include network effects related to price and coverage). Here I evaluate whether the incumbent would compete with an entrant on other margins.

Price schedule. Competing operators could potentially differentiate their plans and pricing in ways not adequately summarized in price levels (for example, one operator might specialize in voice and the other in SMS). However, there is little evidence of such specialization after additional competition entered in Rwanda.[46] The entrant's plans were similar to the incumbent; the incumbent reduced the prices of different services in a nearly proportional manner; and different services appear to grow proportionally between the operators (see Appendix A.1).

[46]With the exception that several years later once smartphones had gained popularity, Operator D specialized in data plans.

TABLE 3. Benchmark Monopoly Simulations (million $)

	Consumer Surplus	**Gov. Revenue**	**Firm Profits**	**Firm Revenue**				
					By Connection			
	All links	All links	All links	All links	Rural-Rural	Rural-Urban	Urban-Rural	Urban-Urban
Baseline	**[244, 270]**	**[65, 73]**	**[102, 118]**	**[165, 187]**	**[30, 33]**	**[17, 18]**	**[24, 28]**	**[95, 108]**
Impact:								
Charge eventual competitive price	**330, 338**	**-2, -4**	**-69, -80**	**-20, -31**	**-4, -5**	**-4, -5**	**-1, -4**	**-11, -18**
... only proximal effect	288, 316	-7, -9	-72, -83	-32, -39	-5, -6	-5, -6	-3, -5	-18, -22
... additional ripple effects	42, 22	5, 4	4, 3	12, 8	2, 2	1, 1	2, 1	7, 4
No rural expansion	**-81, -92**	**-11, -14**	**-15, -22**	**-32, -42**	**-9, -10**	**-4, -4**	**-6. -8**	**-14, -20**
... only proximal effect	-77, -83	-10, -11	-13, -17	-30, -35	-8, -9	-4, -4	-6, -7	-12, -15
... additional ripple effects	-3, -8	-1, -2	-1, -5	-2, -7	-0, -1	-0, -0	-0, -1	-1, -5
Charge eventual competitive price and no rural expansion	**198, 217**	**-10, -11**	**-68, -79**	**-42, -49**	**-10, -10**	**-7, -7**	**-5, -7**	**-20, -25**
... only proximal effect	155, 200	-14, -14	-72, -81	-53, -55	-10, -11	-7, -8	-7, -8	-28, -28
... additional ripple effects	43, 17	4, 3	4, 2	12, 6	1, 1	0, 0	2, 1	8, 4

Quality. The model includes service quality as indicated by coverage, measured by the accessibility of towers in a radius of the locations an individual uses a phone most. To the extent that the expansion of coverage corresponds with other measures of geographical quality (such as the frequency of dropped calls and the availability of airtime from agents), coverage represents a proxy, and the estimation procedure will capture how consumers respond to the combined measure of quality.[47] Several call quality measures are regulated under the terms of each operator's license, and quality tests by the regulator suggest little difference between the operators (see Appendix A.2).

Handsets. In many developed countries, mobile phone operators differentiate themselves based on selection and pricing of handsets. However, in African markets the market for handsets has been relatively independent from the market for mobile service (in 2008 only 3% of phone owners in sub-Saharan Africa had received their handset with a contract, as reported in Table 2). Further, most African operators use the same GSM standard so that the same handset can be set up on any of the networks. In Rwanda, while operators have stores that sell handsets, during the period of my data, operator sales records account for only 10% of total handsets activated. I assume that the entry of an operator would not change the prices or availability of handsets.

Other services. As they spread, mobile phones began to provide additional services beyond voice, including mobile money and internet. However, most of these services either developed later than the period of study, or were not differentiated across operators (see Table 2 and Appendix A.3).

9. The Effects of Competition

This section presents the results of simulations with competition, after an entrant is allowed into the market and consumers are allowed to adjust their adoption, operator, and usage decisions. I report results up to horizon December 2008= $\tilde{T}^{approx}(0.3 \cdot \mathbf{p}^{monopoly}, \boldsymbol{\phi}^{monopoly})$, which spans the competitive outcomes.

[47]The cost model, however, assumes that costs of geographic quality come only from tower construction; it would underestimate costs if correlated dimensions of quality are costly to provide. However, airtime agents operate on commission, earning a proportion of their sales.

Without government intervention, competition does not develop. I consider the results if the incumbent were able to dictate the terms of interconnection (f_{ij}), as is the case with most emerging network goods (such as Facebook and many mobile money systems).[48]

Prior to the pricing game, I allow the incumbent to select from a menu of interconnection rates: f_{ij} between \$0.00 and \$0.54 per minute, and then compute the resulting Nash equilibrium prices and outcomes. I report strategic interactions in normal form for the government regulated level $f_{ij} = \$0.07$ (Tables A2 and A3) and the alternative that leads to the most profitable equilibrium for the incumbent, $f_{ij} = \$0.54$ (Tables A4 and A5).

When given the option, the incumbent will set interconnection rate to \$0.43. Outcomes are shown in Table 4, and do not differ substantially from the monopoly case. (This may rely on the regulatory restriction that operators charge the same prices for on- and off-net calls; in absence of this rule, the incumbent could charge a low price for on-net calls and a high price for the calls to the incumbent's network that incur interconnection fees.) This mimics observed outcomes in many emerging network goods: when one player is dominant, interconnection rarely arises.

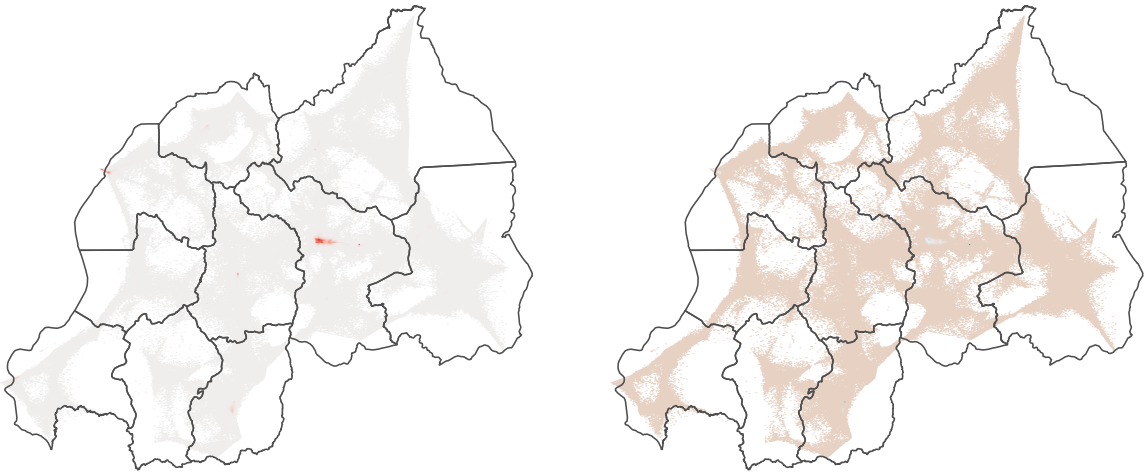
Alternately, if the firms selected an interconnection rate to maximize joint profits, they would select a high interconnection rate of \$0.54 that stalls competition, with outcomes in Table 4. This is similar to theoretical results that suggest that if firms select the interconnection rate, they may use it as an instrument of collusion to sustain high prices (Armstrong, 1998; Laffont et al., 1998).

Adding a competitor under regulated interconnection can dramatically lower prices. If alternately $f_{ij} = \$0.07$, the terms recommended by PwC (2011), the entrant fails to attract large market share, but still induces a substantial effect on price and consumer welfare. The entrant would set prices to 35% of the monopoly level, and the incumbent would reduce prices to 45% of the monopoly level, charging a premium for its better quality network.

Outcomes are shown in Table 4, and the price series is shown in Figure 2.

[48]It is computationally inexpensive to consider different terms of interconnection: conditional on final consumer prices, consumer behavior and associated network effects are fixed.

FIGURE 4. Geographical Revenue Impact of Adding a Competitor



(a) Incumbent (b) Entrant

Blue represents gain; red loss.

Profits reported in that table and figure does not include fixed costs in setting up an operator that are not accounted for in long run incremental costs. Based on PwC (2011), I infer that operators incur fixed costs equal to 50% of their incremental costs. This suggests that the entrant incurs a fixed cost of $6.23m (lower) or $7.57m (upper) of operating over this horizon.

Figure 4 shows the geographic impact of revenue from adding a competitor: the entrant captures revenue in urban centers but pays out interconnection charges in rural areas; the incumbent loses revenue from the urban network.

This policy change would have had an enormous impact on welfare. Over the horizon from 2005-2008, at baseline the monopoly provided a social surplus of $334m (lower) or $386m (upper), corresponding with 2-3% of Rwanda's GDP over the same time period. Adding a competitor under this interconnection rate would increase net social welfare by $200m (lower) or $208m (upper), equivalent to 1.4% of GDP or 6-7% of official development aid in Rwanda over the same period.

Increasing competition mostly increases incentives to invest in rural towers. I next consider whether the incumbent would alter investment in rural towers in

TABLE 4. Competitive Outcomes

Policy			Outcomes (January 2005-December 2008)							
	Inter-connect	Switch. Cost	Prices		Incumbent		Entrant		Gov.	Consumer
					Revenue	Profit	Revenue	Profit	Revenue	Surplus
	f_{ij}	s	$\frac{\mathbf{p}^0}{\mathbf{p}^{mono}}$	$\frac{\mathbf{p}^1}{\mathbf{p}^{mono}}$						
	$/min	$			$m	$m	$m	$m	$m	$m
Baseline: Contested Monopoly	-	-	1.00, 1.00	-	[141, 164]	[108, 126]	[0, 0]	[0, 0]	[58, 66]	[168, 194]
Impact of adding competitor...										
Entering January 2005										
Interconnection rate										
...incumbent profit maximizing	0.54	36	1.00, 1.00	0.80, 0.80	-3, 13	24, 44	-2, -19	-3, -21	-1, -2	8, 11
...initial proposed level (RURA, 2006)	0.09	36	0.50, 0.45	0.45, 0.35	-4, -29	-22, -43	4, 13	-1, -1	2, -1	215, 261
...**revised** glide path start (PwC, 2011)	0.07	36	0.45, 0.45	0.35, 0.35	-23, -33	-38, -47	11, 17	-0, 3	-1, -1	245, 261
...revised glide path end (PwC, 2011)	0.04	36	0.40, 0.40	0.30, 0.30	-37, -50	-53, -65	16, 24	4, 9	-3, -4	271, 293
...bill and keep	0.00	36	0.35, 0.30	0.30, 0.30	-36, -39	-59, -71	10, 0	5, -2	-4, -7	293, 345
...asymmetric	0.07 entrant 0.06 incumbent	36	0.45, 0.45	0.35, 0.35	-22, -32	-37, -46	10, 16	-1, 2	-1, -1	245, 261
	0.07 entrant 0.05 incumbent	36	0.50, 0.45	0.40, 0.35	-16, -31	-29, -45	12, 15	1, 1	1, -1	221, 261
Interconnection rate **revised** + number portability	0.07	19	0.45, 0.45	0.35, 0.35	-26, -37	-40, -50	14, 20	1, 5	-1, -2	246, 262

In outcome cells, first number is outcome in low equilibrium; second in high. Profits omit fixed costs of operation and license fees.

response to competition. While determining the exact towers under a profit maximizing rollout is computationally infeasible, I simulate suggestive counterfactuals, where the incumbent has the option to trim back marginal, low revenue towers.

I first rank each tower z by a proxy of how desirable it was for the firm to build. I rank towers by empirical revenue of the transactions they transmitted ($\bar{R}_z$: 'average direct baseline revenue'). This provides a rough gauge of the desirability of a tower. I propose several cutoffs n and compute the progression of coverage omitting this set of rural towers ($\mathbf{z}_{(n)} = \{z \in \mathbf{z}_{full} | \bar{R}_z > \bar{R}_{(n)}$ or z is urban$\}$, where $\bar{R}_{(n)}$ is the nth order statistic of $\bar{R}$ for rural towers). Given each counterfactual rollout plan (see A1), I compute each individual's time series of coverage $\phi_{it}(\mathbf{z}_{(n)})$, the resulting link utilities and durations, and then simulate a new network adoption partial equilibrium. The change in coverage has an immediate effect on calls: lower coverage increases the hassle cost of placing a call, reducing durations and the utility from calling. Consumers who obtain less utility from calling may also change their adoption decision, which can cause even consumers who were not directly affected by the change in coverage to change their adoption decisions.

To better understand the effect of competition on investment, I decompose the effects on investment in Table 5, by market structure and interconnection rate. Starting from full equilibrium, I simulate adoption partial equilibria where tower investments are removed, and then measure the effect of adding those investments in two stages: first, if consumers cannot change their choice of operator but can adjust adoption dates and usage, and then allowing consumers to change operator (thus capturing incentives for operators to differentiate).

I evaluate the incentives to build out two components of the rollout plan: the 10 lowest revenue rural towers, which were unprofitable under monopoly (Bjorkegren, 2018), and the 50 lowest revenue rural towers, which together were profitable under monopoly.[49] The social return on both of these investments was positive, as shown in the last column of Table 5. This social return increases under competition: these towers see more use when prices are lower and adoption is higher.

[49]One could alternately difference these to report the incentives to build towers 10-50, however that comparison introduces additional noise.

I next consider the private incentives to build these towers. The net effect of competition policy on investment arises from three forces, decomposed for the 50 tower case below:

1. Competition lowers overall revenues. More intense competition lowers prices, so that the revenue obtained from a second of talk time is lower. Under monopoly, investing in towers 1-50 generated a total of $2.57m (lower equilibrium) or $2.46m (upper) of revenue. However, under competition it generated net revenue $1.92m combined between the two operators.

Firms face the same cost for building a tower, or serving a second of calls. Thus, holding fixed consumer and operator choices, under competition a given investment in towers generates lower profits than under monopoly.

2. Competition splits the revenue generated by rural towers... Under competition, not only is total revenue lower; it is now split with another firm. As a result, some benefits of investment spill into the competitor's network. To see this more clearly, consider the outcomes that result when consumers keep the same operator but can adjust adoption and usage in response to the investment ('fixing operator').

2a. ...some revenue accrues at the boundary of the competing network. The investment increases calls from the entrant's network to the incumbent's network, shown in the entrant's off-net column.

Holding fixed operator choices, under an interconnection rate of $0.07/minute, 15% of the revenue from the incumbent's investment in the 50 lowest revenue towers accrues to the border with the entrant's network. These spillovers can partially be recouped with interconnection fees: 10% of the revenue is given back under an interconnection fee of $0.07/minute.[50]

2b. ...some revenue accrues to the interior of the competing network. However, 0.4% (lower) or 1% (upper) of the revenue benefits generated by the incumbent's investment spills over into the interior of the entrant's network–shown in the entrant's on net

[50]Note that theoretically, there can be cases where competition *increases* revenues from this channel: if operators are sufficiently differentiated that the entrant attracts consumers who would not have adopted under the incumbent, and interconnection fees are large enough. However, in this case, the entrant offers an inferior service that is not sufficiently differentiated.

column. Interconnection fees are incurred only at the boundaries of the two networks, and do not adjust for these internal spillovers. In this case, the entrant's network is small, and these interior spillovers are also quite small.

On net, effects 1 and 2 lower the return on investment, so that if consumer operator choices are held fixed, the private return on investment becomes negative for either investment.

3. A business stealing effect increases the incentive to differentiate quality. However, the bulk of revenues generated by the investment under competition arise from a business stealing motive to differentiate quality. This is observed when consumers are allowed to change their choice of operator ('plus operator choice'). Because the investment is valued by subscribers who otherwise would select the entrant's network, it induces many of them to switch to the incumbent. This business stealing effect dwarfs the positive network effects: on net, building additional rural towers tends to reduce the entrant's revenues and profits.

With this business stealing effect, the private returns of investing in these rural towers becomes positive, and is larger than the returns under monopoly.

In general, the balance of these forces–and thus, the effect of competition on incentives to invest–will depend on how preferences interact with the network. Consider an alternate case where consumers did not travel, so that rural consumers valued only rural coverage, and urban consumers valued only urban coverage. Then, rural consumers may only subscribe if the incumbent built out the rural network, but urban consumers would not switch operators based on the rural network. In that case there would no business stealing effect, and competition would tend to lower incentives to invest in towers.

Additionally, the amount of revenue that accrues in the boundary versus the interior of a competing network will depend on which nodes are marginal.

The monopoly benchmark simulations presented in Table 3 diagnose that the business stealing effect is likely to be large here. In particular, under monopoly the building of the rural network draws most revenue from urban-urban connections, even considering only the proximal effect. This suggests that urban consumers value and use rural coverage.

The interconnection rate acts as a dial on the level of competition. Figure 5 shows equilibrium outcomes as a function of the interconnection rate (shown decreasing with the x-axis).[51] Adding a competitor under high interconnection rates results in outcomes similar to monopoly; as the interconnection rate is decreased, equilibrium prices decline and consumer surplus increases. As the interconnection rate is lowered, the incumbent's profits decline and the entrant's profits increase. The effect on incentives to invest is mixed: incentives to build the 50 lowest revenue rural towers decline as the interconnection rate is lowered and the market becomes more competitive.

Number portability increases the level of competition. In some cases, a firm may more easily maintain dominance when it is costly for its customers to switch to competing options. While switching costs are often technological, they can be altered by firm decisions, or through regulation.[52] In the telecom context, a large component of switching costs comes from the need to switch numbers when opening an account with a new operator. In a nationally representative survey, 31% of Rwandans said the reason they have not switched operators is that they would not be able to keep their phone number (Stork and Stork, 2008), and hypothetical responses in my consumer survey suggest that 49% of the cost of switching operators comes from the hassle of changing phone numbers.

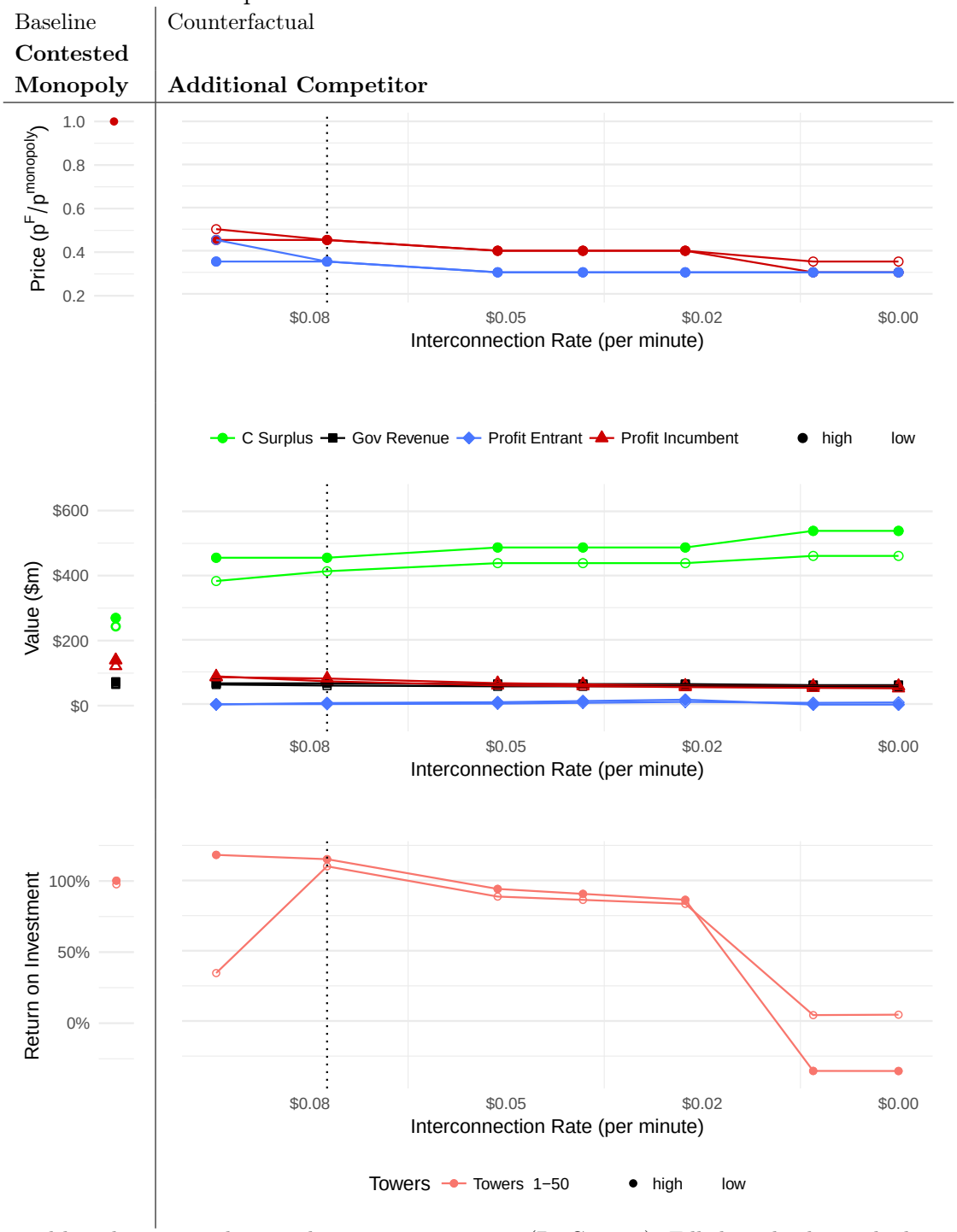
A common telecom policy is number portability: regulators give property rights over phone numbers to consumers, allowing them to transfer their phone numbers when switching operators. However, there are concerns that forcing number portability before a market is mature may reduce investment. In 2013, 25% of developing markets had introduced number portability and 15% were planning to do so in the future (GSMA, 2013). Rwanda initially planned to introduce portability when mobile operators reached combined 60% market penetration, but as of this writing has yet to implement it.

I simulate the effect of introducing number portability, in Table 4. My consumer survey suggests that doing so would reduce the cost of switching operators from $36.09

[51]There are some interconnection rates in this range that do not lead to an ε-equilibrium for this grid resolution and $\varepsilon \leq$\$2m. I omit these from the plot.

[52]For example, Google criticized Facebook for making it difficult to export lists of friends, thus making it more difficult to switch from Facebook to the nascent Google+ social network.

FIGURE 5. Equilibrium Results as Function of Interconnection Rate



Dotted line denotes implemented interconnection rate (PwC, 2011). Filled marks denote high equilibrium and open marks denote low equilibrium. In top two plots, red represents incumbent and blue entrant. Bottom plot shows the incumbent's return on investment for the 50 lowest revenue towers.

TABLE 5. Effect of Competition on Incentives to Invest in the Network

	Inter-connect	Eqm. Prices		Incumbent			Interconnect Fees	Entrant			ROI	
		Incumb.	Entrant	Costs	Revenue			Revenue		Costs		
	Rate f_{ij}	$\frac{\mathbf{p}^0}{\mathbf{p}^{mono}}$	$\frac{\mathbf{p}^1}{\mathbf{p}^{mono}}$		On-net	Off-net calls	←	Off-net calls	On-net		Private	Social
	$/min			$m	$m	$m	$m	$m	$m	$m		
Building towers 1-50												
Contested monopoly	-	**1.00, 1.00**	-	**1.30, 1.23**	**2.57, 2.46**	-	-	-	-	-	**0.98, 1.00**	**6.64, 6.49**
With competitor	**0.07**	**0.45, 0.45**	**0.35, 0.35**	**2.70, 2.79**	**7.85, 8.27**	**-2.54, -2.70**	**0.37, 0.44**	**-1.65, -1.65**	**-1.74, -2.00**	**-1.68, -1.80**	**1.10, 1.15**	**7.85, 8.13**
...fixing operator				1.11, 1.08	0.84, 0.77	0.04, 0.04	0.10, 0.09	0.15, 0.14	0.004, 0.01	0.05, 0.05	-0.12, -0.16	5.86, 5.92
...plus operator choice				1.59, 1.71	7.02, 7.49	-2.59, -2.73	0.27, 0.35	-1.80, -1.78	-1.75, -2.01	-1.74, -1.85	-	-
Building towers 1-10												
Contested monopoly	-	**1.00, 1.00**	-	**0.14, 0.14**	**0.05, 0.07**	-	-	-	-	-	**-0.61, -0.50**	**0.63, 0.87**
With competitor	**0.07**	**0.45, 0.45**	**0.35, 0.35**	**0.22, 0.22**	**0.46, 0.48**	**-0.16, -0.16**	**-0.02, -0.02**	**-0.15, -0.15**	**-0.07, -0.07**	**-0.09, -0.10**	**0.31, 0.32**	**1.33, 1.37**
...fixing operator				0.14, 0.13	0.03, 0.02	0.001, 0.0009	0.005, 0.01	0.01, 0.01	0.0001, 0.00006	0.002, 0.002	-0.76, -0.80	0.97, 0.80
...plus operator choice				0.08, 0.09	0.44, 0.45	-0.16, -0.16	-0.02, -0.02	-0.15, -0.16	-0.07, -0.07	-0.10, -0.10	-	-

In outcome cells, first number is outcome in low equilibrium; second in high. Outcomes computed from January 2005-May 2009. When holding operator choices fixed, consumers who initially switched operators are allowed to change their adoption date for the initial operator but maintain the same switch date. On-net revenues include revenue from extra fees. Interconnect fees represent net payment from entrant to incumbent. Social ROI represents consumer surplus, government revenue, and firm profit, relative to firm costs.

to $18.51 (see Appendix B.2). This results in more consumers using the entrant, which tends to raise entrant profits at the expense of incumbent profits; it results in a small boost in consumer surplus.

10. Conclusion

Societies are grappling with an increasing number of industries characterized by network effects. This paper develops a method to simulate the effects of competition policy in a network industry. I demonstrate how data from an incumbent monopoly can be used to estimate the effects of a variety of competition policies. My method captures how changes ripple throughout networks and across network boundaries, and can thus decompose how the policy environment affects incentives to invest. In addition to the policies demonstrated here, this method can also estimate effect of splitting up an incumbent, under arbitrary splits of customers and assets (although such a policy was not under consideration in this context, it is under consideration in other contexts where this approach could be applied).

I focus my approach on an industry of particular importance to developing societies: mobile phone networks provide the infrastructure (the 'rails') for an increasing array of vital services, including communication and increasingly payments and banking. I find that competition in the Rwandan mobile phone industry has a large scope to affect welfare. I find that policies to increase competition have mixed effects on incentives to invest: they split the revenue generated by rural towers, but this effect is mostly dominated by increased returns from differentiating quality.

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TABLE A1. Operator Differentiators

Phone owners in sub-Saharan Africa*:	2007-2008
Reasons you chose your current operator	
Wider coverage	51%
Most of my friends and family on same network	37%
Range of services	27%
Price	20%
Customer service	15%
Better voice clarity / quality	12%
Company reputation	9%
Free handset with the connection	9%
No other option	5%

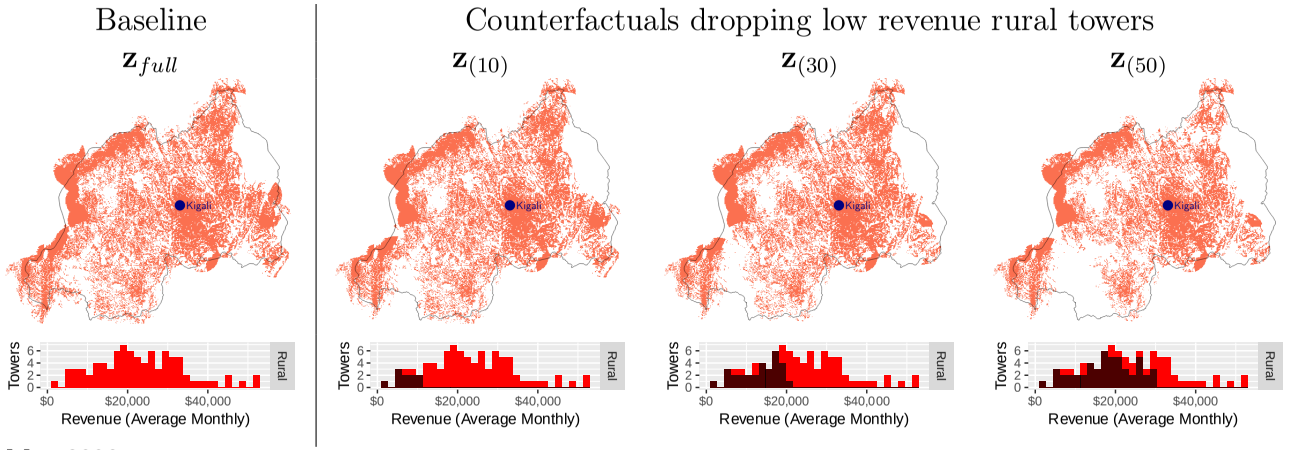
Source: RIA household survey 2007/2008. *: Representative samples of Benin, Botswana, Burkina Faso, Cameroon, Ethiopia, Ghana, Cote d'Ivoire, Kenya, Mozambique, Namibia, Nigeria, Rwanda, Senegal, South Africa, Tanzania, Uganda, and Zambia.

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APPENDIX A. POTENTIAL DIFFERENCES UNDER COMPETITION

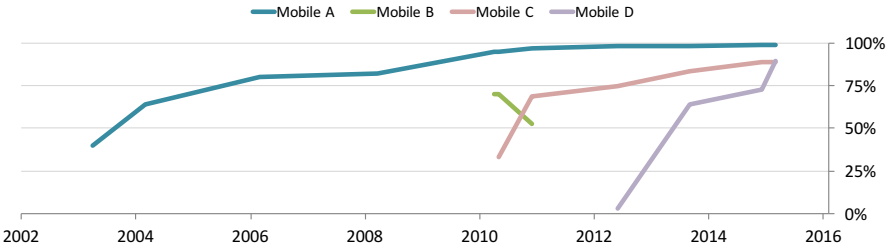
FIGURE A1. Menu of Tower Investments for Incumbent



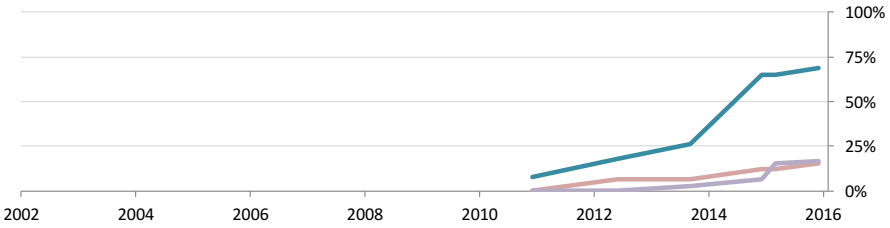
Coverage as of May 2009.

FIGURE A2. Coverage by Technology

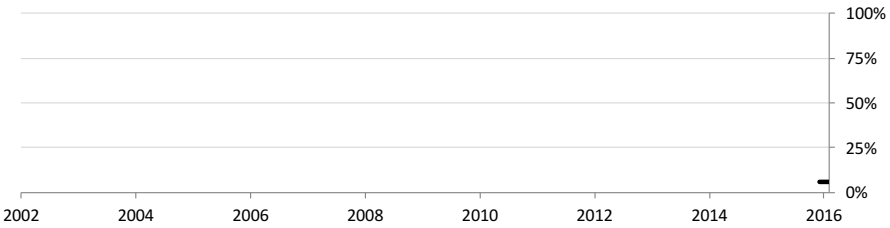
(a) 2G Network



(b) 3G Network (Mobile Internet)



(c) 4G Network (Mobile Broadband): Shared Wholesale Network



	30pct	35pct	40pct	45pct	50pct	55pct	60pct	65pct	70pct	75pct	80pct	Full
30pct	44.57, **-1.47**											
35pct	57.30, -3.59	57.09, **-1.44**										
40pct	**62.98**, -3.89	67.61, -1.92	68.88, **-1.42**									
45pct	62.38, -1.21	**70.63**, **-0.25**	77.02, -0.55	79.48, -1.39								
50pct	58.29, 1.72	67.81, **4.15**	**77.43**, 3.02	**84.95**, 0.56	88.28, -1.37							
55pct	51.13, 4.66	61.81, 8.78	72.26, **9.35**	81.67, 5.38	**89.91**, 0.82	92.01, -1.35						
60pct	43.04, 9.50	53.93, 12.51	65.65, **14.17**	75.67, 12.33	85.68, 6.71	**95.61**, -0.26	96.56, -0.98					
65pct	37.14, 12.38	45.16, 18.14	56.35, **19.73**	67.65, 17.87	77.60, 14.29	90.96, 7.46	**102.06**, -0.15	103.42, -1.30				
70pct	31.17, 16.27	38.10, 22.20	46.68, **26.27**	57.12, 24.65	68.32, 21.45	81.45, 16.87	95.12, 7.85	**105.64**, -0.08	106.65, -0.93			
75pct					57.51, **28.29**	70.80, 24.37	83.07, 17.53	96.46, 8.11	**107.04**, -0.05	108.47, -1.32		
80pct	22.63, 21.22		32.35, 35.31		46.22, **36.24**	58.00, 31.68	70.98, 26.28	84.74, 17.78	98.63, 8.12	**108.61**, -0.02	**109.58**, -0.90	
Full	11.48, 26.56		16.03, 44.75		21.59, 51.47	25.44, 53.70	37.28, **79.49**	36.37, 51.68	44.83, 46.57	56.75, 39.17	88.90, 39.65	**107.35**, -1.24

Incumbent actions in rows; entrant in columns. Cells represent incumbent and entrant profits, in million USD.
Best responses are bolded. Underlined cell represents a Nash Equilibrium.

TABLE A2. Competitive Interaction: Interconnection $0.07 Switching Cost $36 Low Equilibrium -200812 (50pct dark)

	30pct	35pct	40pct	45pct	50pct	55pct	60pct	65pct	70pct	75pct	80pct	Full
30pct	55.44, **-1.55**											
35pct	66.49, -1.71	68.51, **-1.55**										
40pct	**72.03**, -1.58	76.67, **0.71**	78.44, -1.56									
45pct	70.76, 2.09	**79.41**, **3.03**	**83.88**, 0.06	86.46, -1.57								
50pct	65.90, 5.86	76.06, **8.23**	83.81, 3.58	**92.73**, 0.94	96.93, -1.57							
55pct	57.95, 9.48	69.39, **13.43**	78.91, 10.57	90.36, 6.83	**100.97**, 2.16	106.30, -1.58						
60pct	48.91, 15.04	59.86, **18.56**	71.12, 16.33	83.28, 14.63	96.03, 9.83	**108.24**, 3.24	**114.62**, -1.66					
65pct	41.61, 19.15	50.23, **24.75**	60.15, 22.31	73.93, 21.77	87.31, 18.86	101.96, 12.03	114.47, 4.11	**121.50**, -1.58				
70pct	34.98, 23.66	42.06, 29.00	50.01, 29.11	62.40, **29.22**	76.87, 27.00	91.00, 22.41	107.37, 13.48	117.93, 2.34	**122.70**, -1.66			
75pct	30.03, 26.71	35.45, 33.56	41.97, 34.08		64.29, **35.62**	79.48, 31.60	94.15, 25.68	107.04, 13.57	121.37, 0.55	123.84, -1.64		
80pct	26.05, 29.04	30.19, 37.01	35.56, 38.45	42.76, 42.62	52.52, **44.21**	65.95, 41.18	81.85, 35.50	95.22, 25.81	109.02, 12.79	**125.26**, 0.06	**127.14**, -1.67	**127.13**, -1.70
Full	13.91, 34.17		18.87, 48.69		25.78, 61.86	30.45, 66.04	45.85, **100.55**	42.84, 63.53	52.35, 57.34	64.84, 47.28	100.69, 48.32	126.14, -1.61

Incumbent actions in rows; entrant in columns. Cells represent incumbent and entrant profits, in million USD.
Best responses are bolded. Underlined cell represents a Nash Equilibrium.

TABLE A3. Competitive Interaction: Interconnection $0.07 Switching Cost $36 High Equilibrium -200812 (50pct dark)

	30pct	35pct	40pct	45pct	50pct	55pct	60pct	65pct	70pct	75pct	80pct	Full
30pct	42.13, **0.98**											
35pct	111.60, -57.89	54.70, **0.94**										
40pct	170.80, -111.70	118.56, -52.87	66.55, **0.91**									
45pct	186.85, -125.68	174.41, -104.03	125.07, -48.61	77.20, **0.88**								
50pct	191.38, -131.37	186.46, -114.50	176.82, -96.36	125.51, -40.00	86.04, **0.87**							
55pct	**194.31**, -138.52	191.01, -120.43	185.24, -103.63	161.16, -74.11	108.18, -17.46	89.82, **0.85**						
60pct	170.58, -118.04	**192.97**, -126.52	**197.32**, -117.50	170.92, -82.91	147.66, -55.27	97.73, -2.38	94.90, **0.68**					
65pct	155.20, -105.68	170.35, -107.05	193.47, -117.39	**182.13**, -96.61	149.65, -57.76	133.12, -34.70	103.80, -1.89	101.30, **0.82**				
70pct	133.52, -86.09	153.06, -92.76	169.70, -96.74	180.64, -98.87	164.49, -74.72	150.88, -52.56	123.00, -20.03	106.89, -1.33	105.06, **0.66**			
75pct					**167.25**, -81.45	**161.16**, -66.00	135.97, -35.36	125.37, -20.80	107.80, -0.80	106.89, **0.27**		
80pct	101.83, -57.99		131.18, -63.51		145.55, -63.10	157.90, -68.22	**146.24**, -48.98	**125.69**, -23.17	**118.99**, -12.25	109.09, -0.50	108.06, **0.63**	
Full	64.50, -26.47		78.68, -17.90		85.51, -12.45	93.27, -14.13	108.72, **8.06**	112.02, -23.97	116.13, -24.74	**125.60**, -29.68	**131.92**, -3.36	**105.72**, 0.39

Incumbent actions in rows; entrant in columns. Cells represent incumbent and entrant profits, in million USD.
Best responses are bolded.

TABLE A4. Competitive Interaction: Interconnection $0.54 Switching Cost $36 Low Equilibrium -200812 (50pct dark)

	30pct	35pct	40pct	45pct	50pct	55pct	60pct	65pct	70pct	75pct	80pct	Full
30pct	53.41, **0.48**											
35pct	166.59, -101.80	66.54, **0.42**										
40pct	227.35, -156.90	165.02, -87.64	76.52, **0.36**									
45pct	**237.92**, -165.07	222.65, -140.22	142.62, -58.68	84.59, **0.30**								
50pct	237.48, -165.71	**232.36**, -148.08	196.40, -109.02	145.06, -51.38	95.10, **0.26**							
55pct	232.78, -165.35	230.74, -147.91	208.87, -119.39	198.45, -101.26	149.73, -46.60	104.51, **0.21**						
60pct	203.59, -139.64	224.88, -146.46	**214.98**, -127.54	205.48, -107.56	198.74, -92.87	153.88, -42.41	113.34, **-0.38**					
65pct	181.22, -120.46	198.22, -123.23	204.28, -121.82	**210.32**, -114.63	203.61, -97.44	188.81, -74.82	156.76, -38.18	119.78, **0.14**				
70pct	151.09, -92.44	173.19, -102.13	179.57, -100.46	204.53, -112.90	**209.58**, -105.71	202.88, -89.47	185.13, -64.28	139.33, -19.06	121.49, **-0.45**			
75pct	131.96, -75.22	147.10, -78.09	161.37, -85.31		203.83, -103.91	**209.78**, -98.70	201.02, -81.19	175.93, -55.32	127.45, -5.53	122.66, **-0.47**		
80pct	116.88, -61.79	127.06, -59.87	139.85, -65.85	159.44, -74.06	176.64, -79.92	203.67, -96.54	**210.03**, -92.69	**183.11**, -62.09	**161.60**, -39.79	127.41, -2.10	125.99, **-0.52**	**126.05**, -0.61
Full	74.87, -26.79		85.66, -18.10		104.56, -16.93	117.19, -20.70	144.66, **1.74**	142.38, -36.01	151.36, -41.67	**160.11**, -47.98	**170.26**, -21.24	124.69, -0.15

Incumbent actions in rows; entrant in columns. Cells represent incumbent and entrant profits, in million USD.
Best responses are bolded.

TABLE A5. Competitive Interaction: Interconnection $0.54 Switching Cost $36 High Equilibrium -200812 (50pct dark)

A.1. **Plan Offerings.** As one test, I evaluate how the market in Rwanda unfolded. I compare the incumbent's detailed price schedule to the entrant's schedule, Table A6. After the introduction of competition, the incumbent lowered prices to almost match the entrant, in an almost proportional way. Three years after the introduction of competition, the incumbent had a higher price level but identical SMS charges. This suggests that the firms did not target different usage profiles. Other plan characteristics (discount timebands, top up structure) were very similar between entrant and incumbent and did not change much upon the entry of the competitor. Their top up policies differed slightly (minimum top up of 500 RwF for the incumbent which gave 90 days of network access. The entrant offered top ups starting at 300 RwF with 30 days of access, or 1000 RwF with 60 days of network access.

As another test, Figure A3 presents the time series of prices and volumes for calls and SMS. Call and SMS prices follow similar downward trends, and volumes follow similar upward trends.[53]

A.2. **Quality.** Rwandan licenses specify that operators must maintain a dropped call rate below 2%, good voice quality in above 90% of connections, SMS success rate above 95%, a delay between the sending and receiving of SMS of less than 48 hours, network availability above 98% for mobile switching centers, fewer than 3% of customers complaining within 30 days, and above 95% of complaints resolved within 24 hours (Rwanda, 2008). The government has sharply fined operators when quality standards were not met, so these can be thought of as a lower bound on quality. Regulator tests in 2012-2013 reported little difference between the operators: a call setup success rate of 94.7% for operator A vs. 93.7% for operator C; a call drop rate of 0.5% for operator A vs. 1.5% for operator C; and an average call setup time of 6.59 seconds for operator A vs. 6.67 seconds for operator C. Only 12% of surveyed consumers in sub-Saharan Africa list voice quality among the main reasons for choosing their current operator.

[53]The third operator saw a spike in SMS volumes in late 2013; it is unclear if this spike was related to a drop in price in 2012 or some other factor.

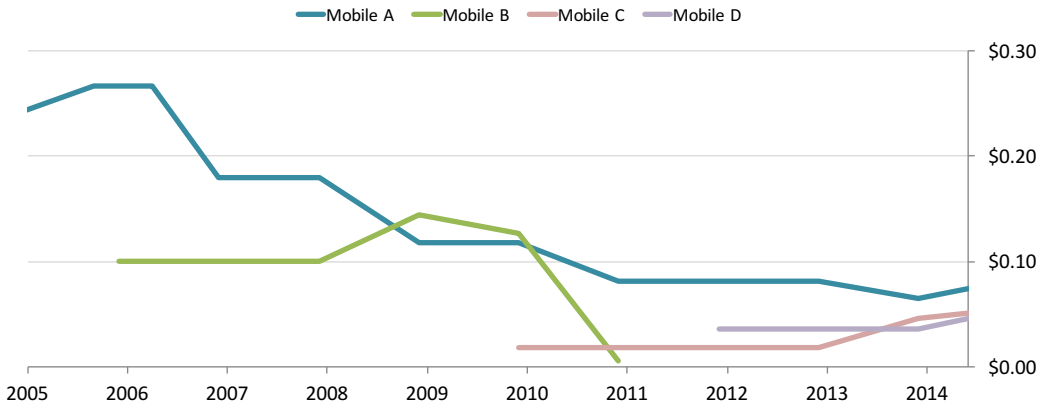
Table A6. Plan Comparison

			Essential Monopoly				Competition between A and C									
		Year	**2006 (baseline)**		**2009**		**2010**				**2013**				**2016**			
		Operator	A		A		A		C		A		C		A		C	
Price	RwF, and percent of baseline per second or message																	
Voice	On Net	Peak	3.3	100%	1.8	55%	1.5	45%	1.5	45%	0.75	23%	0.42	13%	0.62	19%	0.58	18%
		Off-Peak	2.8	100%	1.2	43%	1.1	39%	1	36%	0.55	20%	0.42	15%	-		-	
		Happy Hour	0.9	100%	0.4	44%	0.15	17%	-		0.15	17%	-		0.02	2%	-	
	Off Net	Anytime	3.5	100%	2.1	60%	2.1	60%	1.5	43%	1.5	43%	1.5	43%	0.62	18%	0.58	17%
SMS	On Net		53	100%	30	57%	30	57%	25	47%	10	19%	10	19%	12	23%	11	21%
	Off Net		53	100%	53	100%	53	100%	25	47%	25	47%	25	47%	26	49%	26	49%
Top Ups	Smallest available (RwF)		500/2500		500		500		300/1000		500		300/1000		500		300/1000	
	Validity (days)		0/30+		90		90		30/60		90		30/60		90		30/60	
Timebands	Peak		M-F 5-21 Sat 5-15		M-F 5-15		M-F 5-24		M-F 6-20		M-F 5-24		M-F 6-20		M-Sun 5-23.30		All times	
	Happy Hour		M-Sat 1-5 Sun 0-7 Sun 23-24		M-Sat 0-5 Sun 0-7 M-Sun 23-24		M-Sun 0-5		-		M-Sun 0-5		-		M-Sun 23.30-5		-	
	Off Peak		All other		All other		All other		All other		All other		All other		-		-	

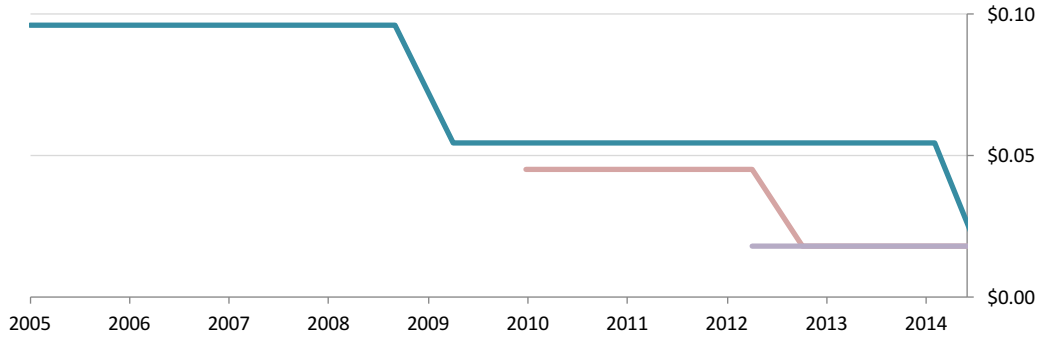
Nominal prices. Source: Archived operator websites (archive.org) and regulator reports. Incumbent also offered a load based pricing plan. Opening an account requires purchasing a SIM card; operator A charged $1.81 for a SIM card preloaded with $0.91 of credit; operator C charged $0.63 for a SIM card preloaded with $0.54 of credit.

FIGURE A3. Calls and SMS Price and Volume Series

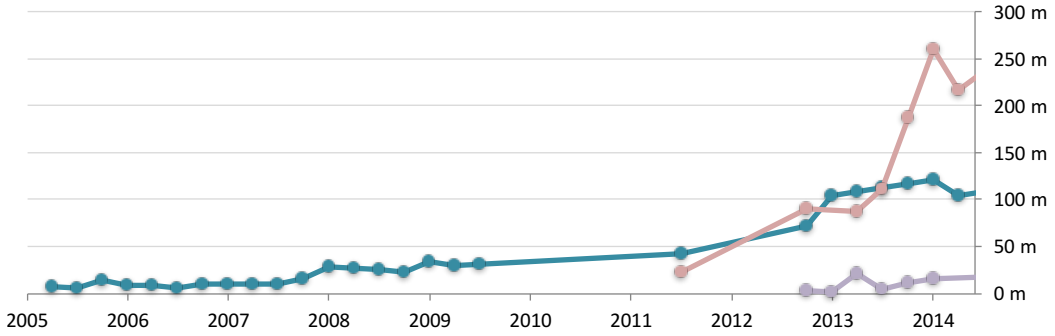
(a) Call Prices (on-network)



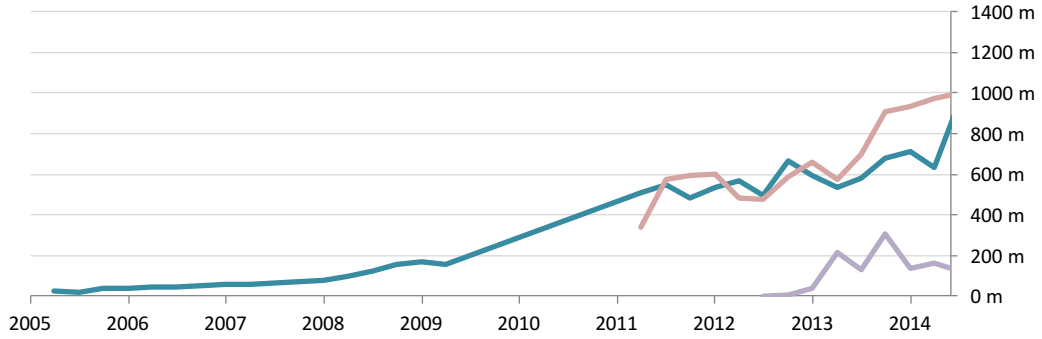
(b) SMS Prices (on-network)



(c) SMS Volumes (quarterly)



(d) Call Volumes (quarterly)



Sources: compiled together from RURA and call records. Omitted outliers from RURA data in 2011 and after 2014.

Airtime sales networks do not appear to be a major source of differentiation (Mann and Nzayisenga (2015) report results on urban airtime sellers). Other aspects of quality do not appear to be a great differentiator across sub-Saharan Africa: only 14.8% list customer service among the main reasons for choosing their current operator (see Table 2).

A.3. **Additional Services.** Mobile money and internet were uncommon at this point. Only 5 sub-Saharan African countries had mobile money systems before 2009, and the first mobile money system in Rwanda launched in 2010 (Mas and Radcliffe, 2011). Mobile internet use was also very low: only 2.5% of sub-Saharan Africans with mobile phones used them to check email in 2007-8 (the only internet usage question asked in that survey round). These services grew after the period of interest; in 2010-11, 18.4% used phones to transfer money, 13.5% to check email, and 17.2% to browse the internet. At present, all major operators in Rwanda offer mobile money and internet. The future introduction of these services would affect individual utilities through the discounted future stream of unobserved benefits in η_i. The development of these additional services would not affect decisions during the period of study, as long as competition does not affect how consumers anticipate the incumbent to provide these services in the future, and consumers do not anticipate the introduction of these services differentially between the two operators.

Consumers also report using mobile phones for activities other than calls, including as a personal organizer (43% of African and 42% of Rwandan phone owners), for games (20% of African and 32% of Rwandan), for music or radio (14% of African and 6% of Rwandan), and for taking photos and videos (15% of African and 5% of Rwandan). However, at this point in time, when these features were available they were typically built in to handsets and not differentiated across operators.[54]

There is a small set of services that could potentially have been differentiated across operators, such as voice mail or call waiting. The incumbent did provide a service to transfer small amounts of airtime credit which could function as a primitive form

[54]For example, many feature phones sold in African markets have radios, and games often came standard with feature phones, such as the popular game Snake included with many Nokia phones.

of mobile money, but it saw little use (see Blumenstock et al., 2016).[55] Many other services were available on all networks. I assume any differentiation arising from these services would have been negligible.

Appendix B. Data Details

B.1. **Cost Data.** I use costs from an interconnection cost study commissioned by the regulator (PwC, 2011). This study captures how network elements, and thus costs, scale with usage. It uses the incremental cost methodology of (World Bank, 2004) based on a bottom-up decomposition.[56] Because of the sensitivity of this data, the study and numeric results are confidential; however, I outline the method here.

From each operator, the regulator requested data on network traffic, capacity, infrastructure, and the cost of replacing each piece of infrastructure (including towers, switches, transmission, and central equipment such as the home location register and voicemail platform).[57] Because these costs are forward looking rather than accounting costs, they represent the cost the operators would have faced to scale up or down. The study consolidates the network design and cost data from Operators A and C, to model a 'generic' operator which lies in between. The authors average responses for most network parameters; when one operator's response deviates from international benchmarks or averaging would be unreasonable, the authors select what is most consistent with prior work. I use these consolidated costs for both operators, which I expect to better capture the costs they would face if competition had entered earlier and they both had reached intermediate scale.

The engineering model proceeds in three steps:

First, for each potential subscriber interaction (such as receiving a call from off network, or placing a call on network), the model notes which pieces of infrastructure it blocks. The model factors in spare and peak load capacity.

[55]Mobile C introduced a feature that plays music while a caller is waiting for the receiver to pick up.

[56]The model itself is encoded as an Excel workbook with 18 worksheets and is described in an accompanying 168 page writeup.

[57]Infrastructure is specified in detail, including the cabinets, software, and batteries for different equipment.

Second, the model computes the unit costs for each piece of infrastructure, including costs of equipment, installation, supervision, taxes, depreciation, land leasing, and capital (weighted average between debt and equity). Any infrastructure that is leased between operators is also accounted for. The regulator uses a version of the model that includes a markup to cover firm fixed costs and license costs; I omit these from incremental costs as I account for them separately.

Third, the model evaluates how total costs would change as usage changes. Because telecommunications costs are lumpy, the marginal cost of an additional second of talk time is typically either zero, or very large. The study instead computes the Long Run Incremental Cost (LRIC), which averages these lumpy costs, to compute the incremental costs of constructing and operating the network to handle each incremental minute of calling.

The regulator commissioned the study to set the interconnection rate (mobile termination rate) and so is primarily interested in the incremental cost of terminating phone calls from another network. For my project, the object of interest is how operator costs change with the scale of the network. Because my counterfactuals can induce substantial change in scale, incremental costs are more empirically relevant than marginal costs. I tailor the incremental cost model to best match the empirical setup. First, many urban towers are capacity constrained, so that operators would build more towers if the network served more calls; however, many rural towers are not: they could serve more calls without substantial investment. I consider rural towers as fixed costs (see Equation 6). From this model I derive incremental costs for six different calls: for both rural and urban calls, the cost of an additional second of calling on-net, placed to a different network, and received from a different network.

B.2. **Consumer Choice Survey.** To determine how consumers select between mobile phone operators, I fielded a consumer survey in Rwanda in summer 2017. 89 respondents were drawn from a convenience sample of mobile phone owners, in a mix of urban and rural sectors near Kigali. Sampling was designed to capture the early adopters contained in my mobile phone data, so was tilted towards higher income areas. The survey was drafted in English and given in Kinyarwanda. 63% of

respondents had an account with the dominant operator by 2009, so they would appear in the initial phone data. See Supplemental Appendix for more details on the demographics of the survey.

In addition to basic usage questions, the survey included questions to calibrate parameters of the model. Respondents were asked to select between two options, where had an additional monetary savings or payment. To find the point of indifference, the monetary savings were varied until the respondent switched his or her choice.

Respondents were asked three questions about switching:

> Imagine your operator had a new discount, but to get the discount you had to set up a new account (entailing replacing your SIM card and transferring any contacts stored on your SIM).

(1) If you could keep your phone number, what is the lowest total amount you would have to save to switch to the new discount? [Selected from a switching form.]
(2) If you had to change to a new phone number, what is the lowest total amount you would have to save to switch to the new discount? [Selected from a switching form.]
(3) If you had to change to a new phone number and switch operators to one of the same quality, what is the lowest total amount you would have to save to switch to the new discount? [Selected from a switching form.]

The first two questions hold fixed the operator. When respondents can keep their phone numbers, they report a mean switching cost of $3.80 (standard error $1.37). If they must switch phone numbers as well, respondents suggested a mean switching cost of $21.38 (standard error $3.06). A large hassle from switching numbers is consistent with other evidence from Rwanda; in a nationally representative survey, 31% of Rwandans said they have not switched operators because they could not keep their phone number (Stork and Stork, 2008). If they must also switch operator, to one of the same quality, they report a mean switching cost of $36.09 (standard error $6.03). Assuming that the cost of switching numbers and operators are additive, the implied cost of switching operators but maintaining the same number is $18.51 (=36.09-(21.38-3.80))—this corresponds to the switching cost under number portability.

Respondents were next asked about idiosyncratic preferences between Operator A and C:

> Now, imagine you had to choose one of two operators from scratch (so you would not need to transfer contacts or switch phone numbers). You may choose either [Operator A], or a new plan that [Operator C] may introduce, New [Operator C], which has the exact same coverage, network, and prices as [Operator A]. (Specifically, a call to an [Operator A] number costs the same whether you are on [Operator A] or New [Operator C].)

(1) What differences would there be between New [Operator C] and [Operator A]? (open ended)
(2) If you had to choose from scratch, which would you choose?
(3) What is the least you would need to save, or highest you would pay, to choose New [Operator C] over [Operator A]? [Respondents were shown a switching form listing the two options on each row and a decreasing amount of savings, and asked when they would switch.]
(4) Why?

Respondents report a mean preference for Operator A of \$2.45 (standard deviation \$6.72).[58] When asked to explain their decisions, 54% of consumers said they preferred the color, ads, or branding of one of the two; 24% mentioned the incumbent had more experience or a better reputation; and 12% cited customer service (including availability of agents and service centers).[59] Preferences for Operator A are not significantly correlated with adoption year, call volumes, length of calls, number of people called, or age. Because they appear to be idiosyncratic, I treat them as random parameters drawn from this distribution.

B.3. **Validating Survey Estimates of Switching Costs.** I do not observe switches between operators in my data; however, they were insignificant in number during this

[58]I omit three respondents who reported extreme idiosyncratic preferences for one of the operators (100x the modal response of +/- 1000 RwF. 2 preferred the incumbent, one the entrant). The respondents quoted typical reasons for preferring one of the two (reputation, usage by family and friends, service), and had typical usage patterns. I believe they misunderstood the exercise.
[59]Only a handful cited feature differences: 3 cited ring back tones (introduced by Operator C but now available on both), 1 cited roaming policies, and 1 cited a loan product introduced in 2017.

period where the main operator was essentially a monopolist. Instead I estimate switching costs through my survey (details in Section B.2). However, in the call data I do observe choices that are similar in nature: the choice of plan on the incumbent. I use the decision to switch plan as a check on my switching cost estimates.

The operator originally offered a single prepaid plan, PerMin, billed by the minute.[60] In February 2006, it introduced another prepaid plan, PerSec, billed by the second. The prices were set so that a minute call under PerMin cost the same as 45 seconds under PerSec. Shorter calls were cheaper under PerSec; longer calls were cheaper under PerMin. Most subscribers place short calls, so the introduction of PerSec represented a substantial price reduction for most. This paper (and Bjorkegren 2018) models the introduction of PerSec as a price reduction, abstracting away from the plan details (pricing under PerMin depends on the distribution of an individual's call lengths). The introduction of the new plan is analyzed in detail in Bjorkegren (2012).

Because the pricing schedule of PerMin depends on the distribution of call durations, I specify a pricing function $p^P(D_{ijt})$ under operator 0 plan $P \in \{M, S\}$, which depends on the distribution of call durations, D_{ijt} and a vector of shocks $\boldsymbol{\epsilon}_{ijt}$.

Then, link ij provides utility $u^P_{ijt}(D_{ijt}) = \frac{1}{\beta_{cost}} \boldsymbol{v}_{ij}(D_{ijt}, \boldsymbol{\epsilon}_{ijt}) - p^P(D_{ijt}) - \beta_{coverage} \phi^0_{it} \phi^0_{jt} D_{ijt}$ (the analogue of Equation 1).

The set of calls that maximize utility under plan P is then $D^{P*}_{ijt} = \arg\max_D u^P_{ijt}(D)$, with associated utility u^{P*}_{ijt}.

Then, i will switch from PerMin to PerSec in period $\tilde{t}$ if:

$$\sum_{t \geq \tilde{t}} \delta^t \sum_{j \in G_i} u^{S*}_{ijt} - u^{M*}_{ijt} \geq s^0$$

and i will remain in PerMin if:

$$\sum_{t \geq \tilde{t}} \delta^t \sum_{j \in G_i} u^{S*}_{ijt} - u^{M*}_{ijt} \leq s^0$$

Note that if in month t, i uses plan P and places calls D^P_{ijt}, the utility gained from instead using plan P' is bounded below by:

$$u^{P'*}_{ijt} - u^{P*}_{ijt} \geq p^P(D^{P*}_{ijt}) - p^{P'}(D^{P*}_{ijt})$$

because the optimal distribution of call durations may change based on the plan.

[60] Calls under the 'per minute' plan were billed by the first minute, and then 30 second increments.

Then for switchers, it must be that:

$$\sum_t \delta^t \sum_{j \in G_i} \left[p^S(D_{ijt}^{S*}) - p^M(D_{ijt}^{S*}) \right] \geq s^0$$

and for nonswitchers, it must be that:

$$\sum_t \delta^t \sum_{j \in G_i} u_{ijt}^{S*} - u_{ijt}^{M*} \leq s^0$$

or, for some $\tilde{s}^0 \geq s^0$,

$$\sum_t \delta^t \sum_{j \in G_i} \left[p^S(D_{ijt}^{M*}) - p^M(D_{ijt}^{M*}) \right] \leq \tilde{s}^0$$

If the adjustment is small ($D_{ijt}^M \approx D_{ijt}^S$) then $\tilde{s}^0 \approx s^0$, and we can estimate s^0 with the objective function:

$$s^0 = \min_s \Bigg[\left| \sum_{i \text{ switcher}} \sum_t \delta^t \sum_{j \in G_i} \left[p^S(D_{ijt}^S) - p^M(D_{ijt}^S) \right] - s \right| + \left| s - \sum_{i \text{ nonswitcher}} \sum_t \delta^t \sum_{j \in G_i} \left[p^S(D_{ijt}^M) - p^M(D_{ijt}^M) \right] \right| \Bigg]$$

This yields an estimate of the switching cost between PerMin and PerSec of \$6.83 (bootstrapped standard error, \$0.03).[61] This estimate is similar to the survey estimate of switching to a discounted plan on the same operator (the first switching question in Section B.2), of \$3.80 (standard error \$1.37). The difference has a t-stat of 2.20, suggesting I fail to reject equality at the 1% level.

Appendix C. Simulation Algorithms

Network Adoption Partial Equilibrium.

Require: firm price paths $\mathbf{p}$ and coverage paths ϕ

Require: candidate adoption path $\mathbf{x}^0$ and operators $\mathbf{a}^0$

$k \leftarrow 0$

repeat

  for each individual i **do**

    for proposed adoption month $t = 0$ to $\bar{T}$ **do**

      for first operator $a = 0$ to 1 **do**

[61] Standard errors computed with 1,000 bootstrap draws.

find optimal switch point $\tilde{t}$, or if not optimal to switch, $\tilde{t} \leftarrow \bar{T}$
$\mathbf{a}_a^* \leftarrow [\underbrace{a \quad a \quad \cdots \quad a}_{\tilde{t} \text{ elements}} \underbrace{(1-a) \quad (1-a) \quad \cdots \quad (1-a)}_{\bar{T}-\tilde{t} \text{ elements}}]$
solve $t_a^* \leftarrow \arg\max_s E_t U_i^{\mathbf{a}_a^*, s}(\mathbf{a}_{G_i}^k, \mathbf{x}_{G_i}^k)$
$u_a^* \leftarrow E_t U_i^{\mathbf{a}_a^*, t_a^*}(\mathbf{a}_{G_i}^k, \mathbf{x}_{G_i}^k)$
end for
$a^* \leftarrow \arg\max_a u_a^*$
if $t = t_{a^*}^*$ **then**
$x_i^{k+1} \leftarrow t$
$\mathbf{a}_i^{k+1} \leftarrow \mathbf{a}_{a^*}^*$
break
end if
end for
$k \leftarrow k + 1$
until $\mathbf{x}^k = \mathbf{x}^{k-1}$
return consumer partial equilibrium path $\mathbf{x}^k$ and operators $\mathbf{a}^k$

For monopoly simulations, operator choices are held fixed to $a = 0$.

Full Equilibrium.

Require: interconnection terms $\mathbf{f}$

$\underline{r}_0, \underline{r}_1 \leftarrow 0.20$
$\bar{r}_0, \bar{r}_1 \leftarrow 1.00$
$k \leftarrow 0$
$\mathbf{p}_0^0, \mathbf{p}_1^0 \leftarrow \mathbf{p}^{monopoly}$
for Δ in $\{0.2, 0.1, 0.05\}$ **do**
repeat
for firm $F = 0$ to 1 **do**
$\mathbf{p}_F^{k+1}, \mathbf{z}_F^{k+1} \leftarrow \arg\max_{\mathbf{p}_F, \mathbf{z}_F} \pi_F(\{\mathbf{p}_F, \mathbf{p}_{-F}^k\}, \{\mathbf{z}_F, \boldsymbol{z}_{-F}^k\}, \mathbf{a}, \mathbf{x}, \boldsymbol{f})$
s.t. $\mathbf{p}_F \in \{\underline{r}_F, \underline{r}_F + \Delta, \underline{r}_F + 2\Delta, ..., \bar{r}_F\} \cdot \mathbf{p}^{monopoly}$
s.t. $\mathbf{z}_0 \in \{\mathbf{z}_{full}, \mathbf{z}_{(10)}, \mathbf{z}_{(20)}, \mathbf{z}_{(30)}, \mathbf{z}_{(50)}\}$
s.t. $\mathbf{z}_1 = \mathbf{z}_{full}$

s.t. $\mathbf{a}, \mathbf{x}$ are a network adoption partial equilibrium given firm price paths $\mathbf{p}$ and coverage paths $\boldsymbol{\phi}(\mathbf{z})$

end for

until $\mathbf{p}_0^{k+1} = \mathbf{p}_0^k$ and $\mathbf{p}_1^{k+1} = \mathbf{p}_1^k$ and $\mathbf{z}_0^k = \mathbf{z}_0^{k+1}$

$\bar{r}_0 \leftarrow \frac{\mathbf{p}_0^k}{\mathbf{p}^{monopoly}} + \Delta$

$\bar{r}_1 \leftarrow \frac{\mathbf{p}_1^k}{\mathbf{p}^{monopoly}} + \Delta$

$\underline{r}_0 \leftarrow \frac{\mathbf{p}_0^k}{\mathbf{p}^{monopoly}} - \Delta$

$\underline{r}_1 \leftarrow \frac{\mathbf{p}_1^k}{\mathbf{p}^{monopoly}} - \Delta$

end for

return firm price paths $\mathbf{p}$ and rollout plans $\mathbf{z}$, and consumer equilibrium path $\mathbf{x}^k$ and operators $\mathbf{a}^k$

Appendix D. The Response of 'Dark' Portions of the Network

Rwanda's complete communication graph includes active nodes that have purchased phones and active links along which calls were placed, as well as latent nodes that could potentially purchase phones and latent links along which calls could potentially be placed if conditions were different. It would be prohibitively costly to gather data on this complete network: it would require a network census of Rwanda that estimated the demand of every *potential* communication link. I use transaction data to observe the active network ($G^T \subseteq \bar{G}$), up to T =May 2009 under monopoly provision. I do not observe links in the latent or 'dark' network. In this section I develop bounds on the behavior of the dark part of the network.

Estimates of an outcome counted up until month $\tilde{T}$ may be biased if either:

(1) There are any nodes i which are not observed in my data (they adopted later under monopoly conditions: $x_i(\mathbf{p}^{monopoly}, \boldsymbol{\phi}(\mathbf{z}^{monopoly}), \mathbf{x}_{-i}^{monopoly}, \mathbf{a}_{-i} = \mathbf{0}, \boldsymbol{\eta}) > T$), who would adopt before $\tilde{T}$ in a counterfactual ($x_i(\mathbf{p}, \boldsymbol{\phi}(\mathbf{z}), \mathbf{x}_{-i}, \mathbf{a}_{-i}, \boldsymbol{\eta}) \leq \tilde{T}$).

(2) There are any links ij which are not observed in my data (there were no calls placed before T under monopoly conditions), which would have become active before $\tilde{T}$ in a counterfactual.

I evaluate results under three approaches.

Naïve approach. This approach reports results up to month $\tilde{T}^{naïve} = T$. Because these results do not include the behavior of the dark part of the network, they may be biased. If latent nodes and links became active, holding prices fixed that would increase incentives to invest in rural towers, because the same cost would generate revenue from more subscribers. Thus, holding prices fixed, such an approach would underestimate the returns to investment under competition. However, the effect on prices is ambiguous.

Conservative approach. The most conservative bound reports results only up until the month $\tilde{T}^{conservative}(\mathbf{p}, \boldsymbol{\phi})$ before the dark network would have preferable adoption and usage conditions. This approach is akin to a counterfactual of speeding up a film using fast forward: if the original film is 5 minutes long, you may run out of tape at 3 minutes: the film could not tell you what happens after those 3 minutes.

I select a limit $\tilde{T}^{conservative}(\mathbf{p}, \boldsymbol{\phi})$ so that the network does not yield more utility before $\tilde{T}^{conservative}(\mathbf{p}, \mathbf{z})$ under counterfactual prices $\mathbf{p}$ and rollout $\mathbf{z}$ than it did at baseline at T:

$$\min_{t \leq \tilde{T}(\mathbf{p},\mathbf{z})} \mathbf{p} \geq \min_{t \leq T} \mathbf{p}_t^{monopoly}$$

$$\max_{t \leq \tilde{T}(\mathbf{p},\mathbf{z})} \boldsymbol{\phi}(\mathbf{z})_t \leq \max_{t \leq T} \boldsymbol{\phi}(\mathbf{z}^{monopoly})_t$$

I do not similarly bound η_1: some individuals in the dark network may have an idiosyncratic preference for the entrant. However, my survey includes individuals in the dark network and finds that idiosyncratic preferences are very slight, and mostly favor the incumbent.

Then under the condition that $\eta_{i1} \leq \eta_{i0}$, each dark node i and link ij faced conditions at least as attractive at T in the baseline as it does in the counterfactual before $\tilde{T}^{conservative}(\mathbf{p}, \mathbf{z})$. Since in the baseline, dark nodes chose to wait until after T to adopt, in a counterfactual they would choose to wait until after $\tilde{T}^{conservative}(\mathbf{p}, \mathbf{z})$. Likewise, any dark links would not become active before $\tilde{T}^{conservative}(\mathbf{p}, \mathbf{z})$. As a result, outcomes reported up until $\tilde{T}^{conservative}(\mathbf{p}, \boldsymbol{\phi})$ will be unaffected by the omission of the dark network.

While this approach is valid, it is conservative and does not fully exploit the variation I observe. The next approach develops a tighter bound using the structural connection between handset and usage prices.

Structural approximate approach. This approach reports up to the month $\tilde{T}^{approx}(\mathbf{p}, \boldsymbol{\phi})$ before the dark network would have preferable adoption conditions, modeling the utility of the dark network using later survey data.

Although competition affects usage prices, it does not affect handset prices, which are offered by a perfectly competitive independent market. The price of a handset represented a major barrier to adoption during this period, and declined dramatically from 2005 to 2011. A subscriber who waited for a large decline in handset prices would be unlikely to subscribe much earlier for a relatively small decline in usage prices. This approach exploits the model to relate the variation in handset prices that was observed under monopoly provision to the variation in usage prices that would be observed under competition.

I use a household survey that is representative of mobile phone subscribers in Rwanda in $T_{survey} = 2011$, several years after my data ends ($N = 350$, conducted by the NGO, Research ICT Africa). The survey includes individuals both in my data (subscribing before May 2009), and in a dark portion of the network (subscribing between May 2009 and 2011).[62] I connect this survey to my model to bound what this dark portion of the network would have done in a counterfactual during the period 2005-2009.

I illustrate the intuition of this approach in Table A7. At the beginning of 2005, an average handset cost $147.73 (quality adjusted index). Individuals who adopted at the beginning of 2011 saved $132.65 by waiting 6 years to adopt, with discounting. In a counterfactual, such an individual would only move forward adoption to the beginning of 2005 if he would have obtained at least $132.65 more in usage utility during those years. However, relative to handset prices, subscribers spend little using their phone, and later subscribers (dark network) subscribers spend less. Individuals who adopted in 2011 spent an average of $2.92 in the month prior to being surveyed. If they had adopted in 2005 and maintained that same level of usage over the next 6 years, that

[62] I assume that individuals that adopted before 2011 still have phones when surveyed in 2011.

TABLE A7. Handset Prices versus Usage

Year	Handset Price Index ($)	Change in Handset Price ($)	For adopters in this year, Mean Airtime Spending Month of Survey in 2011 ($)	Total Number of Mobile Phone Accounts (Regulator)
2005	147.73	-51.05	4.41	138,728
2006	96.68	-34.37	3.39	222,978
2007	62.31	-13.76	4.12	322,561
2008	48.55	-8.66	5.11	554,642
2009	39.88	-3.11	2.81	1,322,637
2010	36.77	-14.14	2.34	2,497,170
2011	22.63	-2.14	2.92	3,548,761

Reported in 2005 US dollars. Handset taxes eliminated July 1. Number of total accounts in Rwanda reported as by the regulator at the beginning each year.

would correspond to total discounted usage of $173.40. However, the mobile phones were much more useful in this later period: as shown in the last column of the table, the network was substantially larger, and coverage was substantially expanded. I next connect this data to my model to evaluate the amount of utility associated with a level of spending on usage, and to approximate changes in the size of network, coverage, and usage prices.

Using survey data, I infer how each individual traded off usage utility against the price of handsets, in the baseline environment. This survey lacks the detailed network information I would need to fully model behavior as in the rest of the paper, so I derive suggestive bounds. For simplicity, I consider individuals receiving service from a single network operator at a price level that corresponds with the competitive price; this will represent a valid bound of behavior under a competitive environment under the condition $\eta_{i1} \leq \eta_{i0}$. For clarity I omit the choice of operator from notation. I assume that in a counterfactual, any individuals measured in the survey (adopting 2009-2011) would adopt prior to any individuals who waited until after 2011 to adopt (and thus are omitted from the survey).

I evaluate the impact of dark nodes by forming lower bounds on each i's adoption date,

$$\underline{x}_i(\mathbf{p}) \leq x_i(\mathbf{p}, \boldsymbol{\phi}, \mathbf{x}_{-i}, \mathbf{a}_{-i}, \boldsymbol{\eta})$$

under counterfactual calling price sequence $\mathbf{p}$. I use two survey questions to evaluate the choices of dark nodes. How long ago the respondent obtained their first mobile phone reveals the baseline adoption date x_i and thus the handset price paid. How much they spent on mobile phone usage in the month prior to the survey reveals the total usage. Under the assumption that all usage is domestic voice, the latter question reveals $p_{T_{survey}} \cdot \sum_{j \in G_i^{T_{survey}} \cap S_{T_{survey}}} d(\epsilon_{ijT_{survey}}, \mathbf{p}_{T_{survey}}, \phi_{iT_{survey}}, \phi_{jT_{survey}}, \mathbf{a}_{T_{survey}})$.[63]

In selecting when to adopt, individuals weigh declines in handset prices against the utility of using the handset. The model implies that the unexplained benefit of using a phone can be derived from considering deviations in adoption. Since x_i is monotonically decreasing in η_i, we simply need an upper bound on $\bar{\eta}_i$. Since $\bar{\eta}_i$ is monotonically decreasing in usage utility, an upper bound $\bar{\bar{\eta}}_i$ can be obtained by using a lower bound for usage utility, $\underline{\mathrm{u}}_{i,x_i-k}(p_{x_i-k})$ for Equation 10. At month $x_i - K$, i must have believed that waiting to adopt until some month $\tilde{K}$ would be preferable:

$$\bar{\eta}_i^0 \leq \bar{\bar{\eta}}_i^0 = \max_{\tilde{K}>0} \left[\frac{1}{1-\delta^{\tilde{K}}} \left[p_{x_i-K}^{handset} - \delta^{\tilde{K}} E_{x_i-K} p_{x_i-K+\tilde{K}}^{handset} - \sum_{s=0}^{\tilde{K}-1} \delta^s E \underline{\mathrm{u}}_{i,x_i-K+s}(p_{x_i-K+s}) \right] \right]$$

The survey asks how many years ago the handset was purchased, so I consider deviations of $K = 12$ months and allow individuals to select between adopting in January of each year.

I assume that the total usage results from calling multiple identical links with parameters equal to the median, and facing the median product of coverage. Then, approximating Equation 3:

$$Eu_{it}(p_t, \boldsymbol{\phi}_t, \boldsymbol{x}) \approx Eu_i^{approx}(p_t, \gamma_t, \boldsymbol{\phi}_t) \coloneqq \gamma_t \cdot |G_i| \cdot Eu_{median}(p_t, (\phi_{it}\phi_{jt})^{median_{ij}})$$

γ_t accounts for growth in the network by scaling the number of contacts by the total number of subscribers on the network at month t.[64] I allow each individual to have a different level of usage, scaled by their approximate number of 'links' $|G_i| = \frac{d_{iT_{survey}}}{d_{T_{survey}}^{median}}$ which I infer from the level of spending. Given the levels of usage prices and coverage, the median link would lead to an expected monthly call duration of $d_{T_{survey}}^{median} = 36.1$ seconds at the time of the survey. I allow the utility of each 'link' to vary with calling

[63] Results would be similar if usage is a combination of services but prices of different services change proportionally with voice prices.

[64] $\gamma_t^{baseline}$ is derived from regulator statistics on mobile subscriptions; see Supplemental Appendix.

prices and coverage, tracking the expected monthly call utility of the median link $Eu_{median}(p_t, \boldsymbol{\phi}_t)$.

I use this mapping to derive bounds on usage utility:

$$\underline{u}_{it} \leq Eu_{it}(p_t, \boldsymbol{\phi}_t, \boldsymbol{x}) \leq \bar{u}_{it}$$

where

$$\underline{u}_{it} \coloneqq Eu_i^{approx}(p_t, \gamma_t^{baseline}, \boldsymbol{\phi}_t)$$

$$\bar{u}_{it} \coloneqq Eu_i^{approx}(p_t, \gamma_t^{eq}, \boldsymbol{\phi}_t)$$

where adoption in a counterfactual may exceed the baseline ($\gamma_t^{eq} > \gamma_t^{baseline}$) due to lower usage prices. (I do not evaluate counterfactuals that increase coverage.) Then, I consider the utility of adopting at month x. Since the optimal x_i decreases in the usage utility and η_i, we can obtain a lower bound of x_i by using the upper bound of both quantities:

$$E_t U_i^x(\mathbf{p}, \boldsymbol{\phi}, \boldsymbol{x}_{G_i}) \leq E_t \bar{U}_i^x(\mathbf{p}, \boldsymbol{\phi}, \boldsymbol{\gamma}^{eq}) = \delta^x \left[\sum_{s \geq x}^{\infty} \delta^{s-x} Eu_i^{approx}(\mathbf{p}_s, \gamma_s^{eq}, \boldsymbol{\phi}_t) - E_t p_x^{handset} + \bar{\bar{\eta}}_i \right]$$

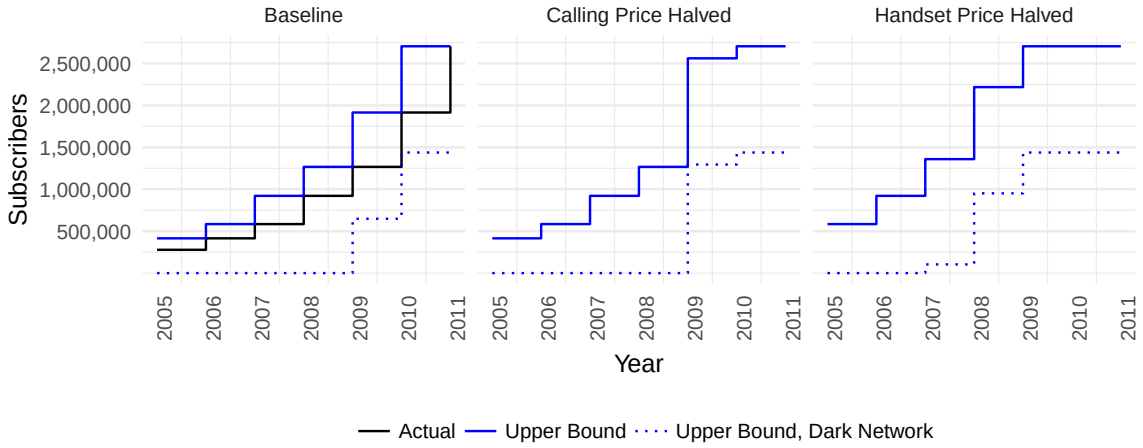
Analogous to Equation 5, a lower bound on i's adoption date is then given by:

$$\underline{x}_i(\mathbf{p}, \boldsymbol{\phi}, \boldsymbol{\gamma}^{eq}) = \min_{x_i} s.t. \left[E_{x_i} \bar{U}_i^{x_i}(\mathbf{p}, \boldsymbol{\phi}, \boldsymbol{\gamma}^{eq}) \geq \max_{s > x_i} E_{x_i} \bar{U}_i^{s}(\mathbf{p}, \boldsymbol{\phi}, \boldsymbol{\gamma}^{eq}) \right]$$

Then $\gamma_t^{eq} = \sum w_i \cdot 1_{\{\underline{x}_i(\mathbf{p}, \boldsymbol{\gamma}^{eq}) \leq t\}}$, where w_i represents the population weight of each individual.[65] To find an upper bound on the dark network's behavior, I solve for equilibrium adoption by starting with an optimistic candidate adoption path ($\boldsymbol{\gamma}^0 = \max \boldsymbol{\gamma}^{baseline}$) and iterating each individual's adoption decision until the process converges to $\boldsymbol{\gamma}^{eq}$.

[65]The total number of accounts implied by the survey data during the earlier period is less than the number present in the phone records. Accounts may be missing from the household survey if respondents misremembered the year of adoption, if they no longer have a phone, or if there are business accounts that were not reported in the household survey. To account for this difference, I multiply survey weights by an adjustment factor, equal to the number of accounts I observe in the data at the end of the last complete year (2008) over the total survey sample weight for individuals who report first obtaining a handset by that year: 2.13. This is valid under the assumption that any missing accounts do not have different usage patterns that those who were surveyed. Alternately, under the assumption that any missing accounts have zero usage, these results are valid without the adjustment factor. Either assumption leads to the same bounds on usage.

FIGURE A4. Dark Network Bounds



The black line represents baseline adoption. The blue lines represent counterfactual adoption: the solid blue line represents total adoption, and dotted blue line represents 'dark' adoption.

I consider counterfactual usage prices during the period of my data; after this period, I assume that calling prices match what ultimately happened.

Figure A4 shows the upper bounds on adoption for all individuals and 'dark network' individuals, for the baseline and two counterfactuals that change prices from 2005-2009. The dark network's adoption is much more sensitive to handset price changes than calling prices: if the calling price were halved, the first adoptions of the dark network would be in 2009; if the handset price were halved, the first adoptions would be in 2007.

I then set $\tilde{T}^{approx}(\mathbf{p}, \boldsymbol{\phi})$ to the last month before the first predicted adoptions of the dark network under counterfactual prices $\mathbf{p}$ and coverage $\boldsymbol{\phi}$. Under the assumptions in this section, dark nodes and links to dark nodes will not affect results prior to $\tilde{T}^{approx}(\mathbf{p}, \boldsymbol{\phi})$. Results may still be affected by latent links between nodes that were active at time: two adopters who did not call each other under monopoly prices may do so under competitive prices. The omission of these links will tend to lower the revenue estimates, and, conditional on prices, lower the estimated returns from investing in towers. I gauge the impact of this omission by comparing results under $\tilde{T}^{approx}(\mathbf{p}, \boldsymbol{\phi})$, which omits these latent links, to those under $\tilde{T}^{conservative}(\mathbf{p}, \boldsymbol{\phi})$, would include the behavior of any latent links.