## COMPETITION IN NETWORK INDUSTRIES:

EVIDENCE FROM THE RWANDAN MOBILE PHONE NETWORK

SUPPLEMENTAL APPENDIX
FOR ONLINE PUBLICATION

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## Part 1. Measurement

## S1. General Measurement

This paper reports most prices in United States Dollars; I convert these from Rwandan Francs (RwF) using the mean exchange rate of 552 RwF to the dollar. ${ }^{1}$ I adjust prices for inflation using the IMF consumer price series for Rwanda, which averaged $9 \%$ inflation per year over this time period.

Accounts. There are 2,092,477 accounts ever referenced in the data, but many do not appear to represent active accounts. For the analysis, I omit the 528,737 accounts that have made fewer than 10 outgoing calls, and 38,679 further accounts for which the time spanned between the first and last observed transaction is less than 90 days (some of these are short term visitors to the country). This results in a sample of 1.5 m accounts.

Account openings and closings. I infer an account as opened the date that the first transaction is made from it. Account are not explicitly closed; prepaid accounts that are not topped up regularly are disabled by the operator but can be used again when next topped up. Some accounts cycle through periods of being disabled but many are used again later; for this reason I ignore the possibility of account closure.

Communication graph (social network). Since the decision to communicate over the phone depends on whether it is possible to communicate in person, the measured call graph is conditioned on individuals' geographic locations. If there were internal migration, these locations would change over time, making it difficult to interpret the measured graph. Permanent internal migration is low in Rwanda over this time period (Blumenstock, 2012).

Adopting a phone may transform an individual's social network - they may keep in touch with friends or family living further away, for example. I uncover the communication graph after any transformation associated with adoption: the graph conditional on phone ownership. The inference in this paper remains valid as long as any such transformation is anticipated and coincides with adoption.

Calling prices. Prior to January 2006, calls were billed by the first minute and each subsequent half minute; after, subscribers could opt in to per second billing (and most quickly did). Modeling the per-minute charges would add significant complexity, so instead
${ }^{1}$ The exchange rate was relatively stable over the period of data (1.2005-5.2009): average of selling and buying price ranged between 543 and 570 RwF to the dollar, National Bank of Rwanda.

I assume these calls were billed at an equivalent per second price, selected to lie between the marginal and average prices to approximate both. I set the per second price to the equivalent charge under the per minute rate when calls are of length 30 seconds.

Raw coverage. I predict the coverage of mobile phone service at each location and time using tower locations and an elevation map. Tower coordinates (latitude and longitude) for most towers were provided by the operator. For those $12 \%$ of towers whose locations are missing from these records, I infer the location based on call handoffs with known towers, using a method detailed in Bjorkegren (2014). I infer the date each tower becomes operational by the date the first transaction that flows through it; I assume that once built, towers are never taken offline. Elevation data is from NASA Shuttle Radar Topographic Mission (SRTM) data, at 90 m resolution; I use the version of the data from Jarvis et al. (2008), which has been processed to fill in data gaps.

If I had more information on the towers (specific equipment, tilt, antenna design), it would be possible to precisely predict coverage with the same commercial packages used by operators for coverage planning. As an approximation I predict coverage based on uninterrupted visibility, using the viewshed tool in ArcGIS. Based on the recommendations of the operator's network planner, I assume the antenna on each tower is located 35 m above the ground, all antennas are omnidirectional, and that the signal has a maximum range of $15 \mathrm{~km} .^{2}$ I threshold the resulting image so that it indicates whether each location has coverage from at least one tower. This provides a raw coverage map for each month, which is my best estimate of the network availability at each location.

I also omit some features of the market:
Handset sharing. Given the high cost of handsets, sharing is common. $55 \%$ of Rwandan phone owners report they allow others to use their handset regularly (Stork and Stork, 2008). An individual may open an account but use it with others' handsets, by inserting their SIM card, but this practice is rare. ${ }^{3}$ It is more common that a person borrows another's

[^1]handset and account. ${ }^{4}$ The model assumes that each node in the network represents a unitary entity such as an individual, firm, or household. I assume that this entity weighs the communication benefits accruing to the node against the cost of adoption, and that the communication graph is fixed over time. If multiple people use a particular phone, then the node will represent their aggregate demand. The model will correctly account for this demand if the composition of people using a particular phone is fixed over time and the adoption decision takes into account the utility of all users (for example, if the owner internalized the benefits of other users' calls through side payments). If the composition of people using a particular phone changes in response to adoption (say, if a couple initially shares a phone but later obtains separate phones and splits its communication), then the communication graph I estimate will be similar to a weighted average of the underlying networks. In that case, during simulations the nodes will not account for changes in usage when borrowers obtain their own phones, nor coordination of adoption times between the nodes.

Text Messages and Missed Calls. I do not explicitly model utility from text messages and missed calls. From the data it is not possible to match the sender and receiver of a given text message. Though important in other contexts, in Rwanda texts were expensive ( $\$ 0.10$, the same as a call of 24 seconds under the lowest peak price, constant from 2005-2009) and represented less than $13 \%$ of revenue and $16 \%$ of transactions. If different relationships use different modes of communication, this omission will underweight the importance of text and missed-call relationships in the adoption decision. The data suggests that the different modes pick up slightly different relationships: the correlation between a node's total calls and texts is $0.53^{5}$, and the correlation between calls and call attempts within a link is 0.58. There appears to be little substitution between communication modes as calling prices change.

Other Omissions. I omit the cost of charging a phone (the four most popular handsets have more than two weeks of battery life on standby). Accounts must be topped up with

[^2]a minimum denomination of credit (the minimum was $\$ 0.90$ by the middle of the data); I treat these charges as continuous rather than lumpy.

Discount rate. I set the discount factor to the inverse of the average real interest rate in Rwanda over this period: $\delta=\left(\frac{1}{1.07}\right)^{1 / 12} \sim 0.9945$ (source: World Bank). I assume that the government, firms, and consumers discount at the same rate. ${ }^{6}$

## S2. Household Surveys

In the paper I report background statistics from several household surveys.
S2.1. Nationally Representative Surveys. For these surveys I apply nationally representative sampling weights.

Demographic and Health Survey 2005 and 2010 (DHS). These are representative surveys of 10,272 (2005) and 12,540 (2010) Rwandan households, asking about demographics, ownership of goods, and use of services (electricity, water, phone, radio, television).

Rwandan Household Survey 2005-6 and 2010-11 (EICV 2 and 3). These are representative surveys of 6,900 (2005) and 7,354 (2010) Rwandan households, asking about demographics and consumption.

Research ICT Africa Household Survey 2007-8 (Stork and Stork, 2008) and 2010-11 (RIA, 2012). These are representative surveys of 1,078 (2007-8) and 1,200 (201011) Rwandan households (201, and 386 with phones), asking questions about information technology for one randomly selected household member. They are used to provide background on how phones are used in this context throughout the text.

S2.2. 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

[^3]Table S1. Survey Demographics
Comparison to Nationally Representative Survey

| Subset: | Owned phones by | 2017 | 2011 |  | 2008 |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | My Survey | My Survey | RIA (2012) | My Survey | RIA (2012) |
| Age |  | 30.0 | 32.3 | 29.3 | 35.2 | 32.6 |
| Male |  | 60\% | 62\% | 57\% | 69\% | 41\% |
| Education | Tertiary | 24\% | 26\% | $4 \%$ | 22\% | 8\% |
|  | Secondary | 57\% | 53\% | $38 \%$ | 53\% | 51\% |
|  | Primary | 16\% | 16\% | 46\% | 20\% | 35\% |
|  | None | $3 \%$ | $4 \%$ | 13\% | $4 \%$ | $6 \%$ |
| Read a letter or newspaper easily |  | 100\% | 100\% | 77\% | 100\% | $86 \%$ |


operator by 2009, so they would appear in the initial phone data. The survey asked questions about demographics, mobile phone usage, and posed several hypothetical questions designed to isolate key parameters.

Demographics and Usage. Table S1 compares demographics between phone owners in my consumer choice survey and a nationally representative survey fielded in 2010-2011 (RIA, 2012). Because the two surveys were fielded at different times, and later than the phone data on which my study is based, the set of consumers owning phones will differ. The first column presents the raw survey results. The second set of columns compares the demographics of consumers who adopted phones by 2011 in my survey and in RIA (2012). The final set of columns compares demographics for consumers who adopted phones by 2008, the last full year of transactions I observe. My sample is of a similar age but is more highly educated (it especially has a large fraction of individuals with tertiary education), though the difference attenuates slightly as the sample is restricted to earlier adopters.

Estimating Parameters. Respondents were asked to select between two options, where one 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). ${ }^{7}$
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). ${ }^{8}$ 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 a normal distribution with this mean and standard deviation.

S2.3. Validating Survey Estimates of Switching Costs. I do not observe switches between operators in call data. However, 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 survey switching cost estimates.

The operator originally offered a single prepaid plan, PerMin, billed by the minute. ${ }^{9}$ In February 2006, it introduced another prepaid plan, PerSec, billed by the second. Shorter calls (typically 45 seconds and below) 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 Björkegren 2019) 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).

[^4]Because the pricing schedule of PerMin depends on the distribution of call durations, I specify a pricing function $p^{P}\left(D_{i j t}\right)$ under operator $I$ plan $P \in\{M, S\}$, which depends on the distribution of call durations, $D_{i j t}$ and a vector of shocks $\boldsymbol{\epsilon}_{i j t}$.

Then, link $i j$ provides utility $u_{i j t}^{P}\left(D_{i j t}\right)=\frac{1}{\beta_{c o s t}} \boldsymbol{v}_{i j}\left(D_{i j t}, \boldsymbol{\epsilon}_{i j t}\right)-p^{P}\left(D_{i j t}\right)-\beta_{\text {coverage }} \phi_{i t}\left(\mathbf{z}^{I}\right) \phi_{j t}\left(\mathbf{z}^{I}\right) D_{i j t}$ (the analogue of Equation 1 in the main paper).

The set of calls that maximize utility under plan $P$ is then $D_{i j t}^{P *}=\arg \max _{D} u_{i j t}^{P}(D)$, with associated utility $u_{i j t}^{P *}$.

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

$$
\sum_{t \geq \tilde{t}} \delta^{t} \sum_{j \in G_{i}}\left(u_{i j t}^{S *}-u_{i j t}^{M *}\right) \geq s^{0}
$$

and $i$ will remain in PerMin if:

$$
\sum_{t \geq \tilde{t}} \delta^{t} \sum_{j \in G_{i}}\left(u_{i j t}^{S *}-u_{i j t}^{M *}\right) \leq s^{0}
$$

Note that if in month $t, i$ uses plan $P$ and places calls $D_{i j t}^{P}$, the utility gained from instead using plan $P^{\prime}$ is bounded below by:

$$
u_{i j t}^{P^{\prime} *}-u_{i j t}^{P *} \geq p^{P}\left(D_{i j t}^{P *}\right)-p^{P^{\prime}}\left(D_{i j t}^{P *}\right)
$$

because the optimal distribution of call durations may change based on the plan.
Then for switchers, it must be that:

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

and for nonswitchers, it must be that:

$$
\sum_{t} \delta^{t} \sum_{j \in G_{i}}\left(u_{i j t}^{S *}-u_{i j t}^{M *}\right) \leq s^{0}
$$

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

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

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

$$
\begin{array}{r}
s^{0}=\min _{s}\left[\quad\left|\sum_{i \text { switcher }} \sum_{t} \delta^{t} \sum_{j \in G_{i}}\left[p^{S}\left(D_{i j t}^{S}\right)-p^{M}\left(D_{i j t}^{S}\right)\right]-s\right|+\right. \\
\left.\left|s-\sum_{i \text { nonswitcher }} \sum_{t} \delta^{t} \sum_{j \in G_{i}}\left[p^{S}\left(D_{i j t}^{M}\right)-p^{M}\left(D_{i j t}^{M}\right)\right]\right|\right]
\end{array}
$$

This yields an estimate of the switching cost between PerMin and PerSec of $\$ 6.83$ (bootstrapped standard error, $\$ 0.03) .{ }^{10}$ This estimate is similar to the survey estimate of switching to a discounted plan on the same operator (the first switching question in Section S2.2), 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.

## S3. 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. ${ }^{11}$ 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). ${ }^{12}$ 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

[^5]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.

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 annualized fixed costs per period (see firm cost equation). From this model I derive incremental costs for six different network interactions: 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.
(Rwanda also has a small number of landline phones (roughly 25,000 lines over this period, $1 \%$ of the size of the mobile network at the end of this period), representing less than $1 \%$ of

Table S2. Operator Differentiators
Phone owners in sub-Saharan Africa*: 2007-2008

| Reasons you chose your current operator |  |
| :--- | :--- |
| Wider coverage |  |

Most of my friends and family on same network $37 \%$
Range of services $\quad 27 \%$
Price $\quad 20 \%$
Customer service $\quad 15 \%$
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.
call volumes with the mobile network. Reported costs also factor in the incremental costs of connecting calls to these lines.)

## Part 2. Model and Simulation Background

## S4. Operator Differentiators

This section evaluates how sufficiently the model estimated in the baseline environment captures behavior under competition. The model imposes constraints on how operators compete, and how consumers respond. In particular, I require that the individual types for the incumbent $\eta_{i}^{I}$, and the latent call graph $\left(\mu_{i j}, \sigma_{i}, q_{i}\right)$ are stable upon the introduction of competition.

To evaluate these assumptions I use two kinds of evidence. First, since Rwanda eventually did admit a viable competitor, I use my original consumer choice survey, other surveys, and official statistics after that competitor's entry in 2009. Second, I report evidence from other African countries that had competitive markets during this time.

The model captures competition on coverage and price levels (which may include network effects related to price and coverage). I first consider the coverage strategies that operators may employ, and then consider other potential margins of competition.

Table S2 presents survey results describing the reasons consumers give for selecting their operator.

S4.1. Coverage. I next consider the coverage strategies that operators employ in different countries.

I obtain a database of cellular tower locations from OpenCelliD, and focus on towers providing voice (GSM) coverage. ${ }^{13}$ Towers are listed with an anonymous identifier representing the operator. I approximate the coverage around each tower with a 15 km buffer, and join the buffers by operator.

I show these approximate coverage maps with a different color for each operator, in Figure S1 for East Africa as of 2019.

Two features are fairly common. First, more operators serve cities than rural areas (in particular, the capitals of Uganda, Kenya, Tanzania, and Burundi are served by many operators). As a result, there is more competition in cities. Second, for the most part, operators are rank ordered in terms of coverage. One operator offers the most coverage, and others offer what appear to be approximate subsets. For the most part, operators do not divide up the country by region. ${ }^{14}$

These patterns are not as visible in Rwanda. Rwanda is a dense country, and has achieved near universal cellular coverage. Starting in 2011, Rwanda forced the incumbent to share its physical towers with competitors at cost. Given this regulation, the competing operators offer comparable coverage. The counterfactual exercises in the paper do not apply this regulation, so one would not expect the entrant to have as extensive rural coverage.

The incumbent built towers culminating in covering $95 \%$ of the country's land area. According to the incumbent's network engineer, the firm prioritized locations based on population density. In the paper, I rank the desirability of these eventually built tower locations using a summary population measure, by computing the number of people living within 10 km of the tower (this radius includes those who will be best served by the tower), using gridded population for year 2000 from Worldpop (2017).

As shown in Table S3, this is substantially correlated with alternate measures, with Spearman rank correlations above 0.43 .

- Consumption. I compute the total consumption of households living within 10 km of the tower, using consumption by district from the representative 2010 NISR EICV

[^6]Figure S1. Coverage in East Africa (GSM, 2019)


Uganda


Rwanda


Burundi
Coverage approximated by 15 km circular buffers around each tower that is listed in the OpenCelliD database as of May 2019. Each color represents a different operator.

3 survey. I assume that consumption is uniformly distributed within each district.
This represents a measure of the wealth of an area.

- Baseline Revenue. The average monthly revenue earned by that tower under baseline adoption and usage.

Table S3. Correlation of Tower Desirability Measures


Spearman rank correlations in cells.

S4.2. Plan Offerings. 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 text messages). However, there is little evidence of such specialization after additional competition entered in Rwanda. ${ }^{15}$ I compare the incumbent's detailed price schedule to the entrant's schedule, Table S4. 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 text message 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. There were small discounts for topping up in large amounts but these were rarely used.

As another test, Figure S2 presents the time series of prices and volumes for calls and texts. Call and text prices follow similar downward trends, and volumes follow similar upward trends. ${ }^{16}$

[^7]Table S4. Plan Comparison
Competition between $A$ and $C$


Figure S2. Calls and Text Price and Volume Series
(a) Call Prices (on-network)

(b) Text Message Prices (on-network)

(c) Call Volumes (quarterly)

(d) Text Message Volumes (quarterly)


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

S4.3. Quality. 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.

Rwandan licenses specify that operators must maintain a dropped call rate below $2 \%$, good voice quality in above $90 \%$ of connections, text message success rate above $95 \%$, a delay between the sending and receiving of text messages 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.

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 S2). ${ }^{17}$

S4.4. 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

[^8]benefits in $\eta_{i}$. 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. ${ }^{18}$

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 of mobile money, but it saw little use (see Blumenstock et al., 2016). ${ }^{19}$ Many other services were available on all networks. I assume any differentiation arising from these services would have been negligible.

## S5. Dark Network

As described in the paper, I do not necessarily observe $\bar{G}$, the full communication graph of Rwanda. I observe individuals who subscribed by the end of my data under the incumbent $\left(S_{T} \subseteq N\right)$ and infer that $i$ and $j$ are linked if $i$ has called $j$ by period $T$. That is, I observe the subgraph $G^{T} \subseteq \bar{G}^{T} \subseteq \bar{G}$. This section considers how dark nodes or links outside this subgraph could affect results.

This section first considers how the existence of dark links could affect estimates. It then models the behavior of the dark network, to guide the selection of the horizon of simulations, $\tilde{T}$.

S5.1. Effect of Dark Links on Estimates. This section follows Björkegren (2019).
Here I consider the potential impact of missing links between nodes within the subgraph I observe.

[^9]Missing links could potentially affects my estimates and all counterfactuals. Based on a representative household survey, $90 \%$ of subscribers report that most calls are to family and friends, and $94 \%$ report that the main purpose of the last 10 calls was social (Stork and Stork, 2008). However, because I infer links from calls, there may be subscribers who $i$ would potentially call, but who he did not call by the time my data ends $\left(j \in \bar{G}^{T} \backslash G^{T}\right)$. The omission of these latent links does not introduce a clear bias in overall call utility, due to the law of iterated expectations: while I observe only links $i j \in G^{T}$ that receive a call before $T$, their shock distributions $\epsilon_{i j t}$ are estimated conditional on receiving a call before $T$. Both forces are counterbalanced in computing the utilities $u_{i t}$; their net effect will depend on the curvature of the functions. In counterfactuals that make calling across each link ij more attractive, utilities will be underestimated, because this would undo the counterbalance: some links that I do not observe would become more attractive. This would suggest I am likely to underestimate the benefits of lowering prices. ${ }^{20}$

Relatedly, one of the benefits of owning a phone is the option value of being able to place calls, which may be valued even if the option is not realized. An extreme example would be a phone purchased solely for emergency use, which provides expected utility even though it may never be used. Theoretically, option value could be over entire links (e.g., to ambulances, fire, police, roadside assistance, nurse call lines). However, in Rwanda, there is little in the way of formal emergency response and emergency calls are likely to be directed to close contacts to whom nonemergency calls are also placed. As a result, valued links are less likely to be missing from the network I measure. Since the utility computed in this model relies on realized calls, any option value would necessarily be underweighted in the call model, though it would be captured in an individual's type $\eta_{i}^{I}$ in the adoption decision. In a robustness check, Björkegren (2019) finds that the value of communication implied by the adoption decision (estimated using instrumental variables) corresponds with that implied by observed calling decisions, suggesting any omitted option value is minor.

S5.2. Modeling the Dark Network for Simulations. 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

[^10]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 the baseline. 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 through horizon $\tilde{T}$ may be biased if either:
(1) There are any nodes $i$ which are not observed in my data (they adopted later under baseline conditions: $\left.x_{i}\left(\mathbf{p}^{\text {base }}, \mathbf{z}^{\text {base }}, \mathbf{x}_{-i}^{\text {base }}, \mathbf{a}_{-i}=\boldsymbol{I}, \boldsymbol{\eta}\right)>T\right)$, who would adopt before $\tilde{T}$ in a counterfactual $\left(x_{i}\left(\mathbf{p}, \mathbf{z}, \mathbf{x}_{-i}, \mathbf{a}_{-i}, \boldsymbol{\eta}\right) \leq \tilde{T}\right)$.
(2) There are any links $i j$ which are not observed in my data (there were no calls placed before $T$ under baseline conditions), which would have become active before $\tilde{T}$ in a counterfactual.

I consider three approaches.

Full horizon. This approach reports results up to horizon $T$. 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 ROI under competition. However, the effect on prices is ambiguous, and thus so is the overall effect on ROI.

Conservative approach. The most conservative bound reports results only up until the month before the dark network would have seen 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 $\tilde{T}^{\text {conservative }}(\mathbf{p}, \mathbf{z})$ so that the network does not yield more utility under counterfactual prices $\mathbf{p}$ and rollout $\mathbf{z}$ than it did at baseline at $T$ :

$$
\begin{gathered}
\min _{t \leq \tilde{T}^{\text {conservative }}(\mathbf{p}, \mathbf{z})} \mathbf{p} \geq \min _{t \leq T} \mathbf{p}_{t}^{\text {base }} \\
\max _{t \leq \tilde{T}^{\text {conservative }(\mathbf{p}, \mathbf{z})}} \boldsymbol{\phi}_{t}(\mathbf{z}) \leq \max _{t \leq T} \boldsymbol{\phi}_{t}\left(\mathbf{z}^{\text {base }}\right)
\end{gathered}
$$

Then under the condition that $\eta_{i}^{E} \leq \eta_{i}^{I}$, each dark node $i$ and link $i j$ faced conditions at least as attractive at $T$ in the baseline as it does in the counterfactual before $\tilde{T}^{\text {conservative }}(\mathbf{p}, \mathbf{z}) .^{21}$ Since in the baseline, dark nodes chose to wait until after $T$ to adopt, in a counterfactual they would choose to wait until after this period. Likewise, any dark links would not become active before this period. As a result, outcomes reported up until $\tilde{T}^{\text {conservative }}(\mathbf{p}, \mathbf{z})$ will be unaffected by the omission of the dark network for prices $\mathbf{p}$ and rollout $\mathbf{z}$.

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 $\tilde{T}^{\text {structural }}(\mathbf{p}, \mathbf{z})$ before the dark network would have preferable adoption conditions, modeling the utility of the dark network using later survey data. Under the assumptions of the model, before $\tilde{T}^{\text {structural }}(\mathbf{p}, \mathbf{z})$ dark nodes and any links to dark nodes will not affect results. (Dark links between observed nodes could potentially affect results; I discuss later here.)

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 baseline 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 $T_{\text {survey }}=2011$, 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
${ }^{21}$ I do not similarly bound $\eta^{E}$ since my survey indicates idiosyncratic preferences are very slight, and mostly favor the incumbent.

Table S5. Handset Prices versus Usage

| Year | Handset Price <br> Index | Change in <br> Handset Price | For adopters in this year, <br> Mean Airtime Spending <br> Month of Survey in 2011 | Total Number of <br> 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.

May 2009), and in a dark portion of the network (subscribing between May 2009 and 2011). ${ }^{22}$ 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 S5. 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) 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 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.

[^11]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 $\eta_{i}^{E} \leq \eta_{i}^{I}$. 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,

$$
\underline{x}_{i}(\mathbf{p}) \leq x_{i}\left(\mathbf{p}, \mathbf{z}, \mathbf{x}_{-i}, \mathbf{a}_{-i}, \boldsymbol{\eta}\right)
$$

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 $p_{T_{\text {survey }}}$. $\sum_{j \in G_{i}^{T_{\text {survey }}} \cap S_{T_{\text {survey }}}} d_{i j}\left(\epsilon_{i j T_{\text {survey }}}, \mathbf{p}_{T_{\text {survey }}}, \mathbf{z}_{T_{\text {survey }}}, \mathbf{a}_{T_{\text {survey }}}\right) .{ }^{23}$

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 $\eta_{i}$, we simply need an upper bound on $\bar{\eta}_{i}$. Since $\bar{\eta}_{i}$ is monotonically decreasing in usage utility, an upper bound $\overline{\bar{\eta}}_{i}$ can be obtained by using a lower bound for usage utility, $\underline{\mathrm{u}}_{i, x_{i}-k}\left(p_{x_{i}-k}\right)$ for Equation 10. At month $x_{i}-K, i$ must have believed that waiting to adopt until some month $\tilde{K}$ would be preferable:

$$
\bar{\eta}_{i}^{I} \leq \bar{\eta}_{i}^{I}=\max _{\tilde{K}>0}\left[\frac{1}{1-\delta^{\tilde{K}}}\left[p_{x_{i}-K}^{\text {handset }}-\delta^{\tilde{K}} \mathbb{E}_{x_{i}-K} p_{x_{i}-K+\tilde{K}}^{\text {handset }}-\sum_{s=0}^{\tilde{K}-1} \delta^{s} \mathbb{E}_{\mathbf{u}_{i, x_{i}-K+s}}\left(p_{x_{i}-K+s}\right)\right]\right]
$$

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.

[^12]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:

$$
\mathbb{E} u_{i t}\left(p_{t}, \mathbf{z}_{t}, \boldsymbol{x}\right) \approx \mathbb{E} u_{i}^{\text {approx }}\left(p_{t}, \gamma_{t}, \mathbf{z}_{t}\right):=\gamma_{t} \cdot\left|G_{i}\right| \cdot \mathbb{E} u_{\text {median }}\left(p_{t},\left(\phi_{i t}\left(\mathbf{z}_{t}\right) \phi_{j t}\left(\mathbf{z}_{t}\right)\right)^{\text {median }_{i j}}\right)
$$

$\gamma_{t}$ accounts for growth in the network by scaling the number of contacts by the total number of subscribers on the network at month $t .^{24} \mathrm{I}$ allow each individual to have a different level of usage, scaled by their approximate number of 'links' $\left|G_{i}\right|=\frac{d_{i T_{\text {survey }}}}{d_{T_{\text {surveney }}}^{\text {men }}}$ 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 $d_{T_{\text {survey }}}^{\text {median }}=36.1$ seconds at the time of the survey. I allow the utility of each 'link' to vary with calling prices and coverage, tracking the expected monthly call utility of the median link $\mathbb{E} u_{\text {median }}\left(p_{t}, \boldsymbol{\phi}_{t}\right)$.

I use this mapping to derive bounds on usage utility:

$$
\begin{aligned}
\underline{\mathrm{u}}_{i t} & \leq \mathbb{E} u_{i t}\left(p_{t}, \mathbf{z}_{t}, \boldsymbol{x}\right) \leq \bar{u}_{i t} \\
\underline{\mathrm{u}}_{i t} & :=\mathbb{E} u_{i}^{\text {approx }}\left(p_{t}, \gamma_{t}^{\text {baseline }}, \mathbf{z}_{t}\right) \\
\bar{u}_{i t} & :=\mathbb{E} u_{i}^{\text {approx }}\left(p_{t}, \gamma_{t}^{e q}, \mathbf{z}_{t}\right)
\end{aligned}
$$

where adoption in a counterfactual may exceed the baseline $\left(\gamma_{t}^{e q}>\gamma_{t}^{\text {baseline }}\right)$ due to lower usage prices. Then, I consider the utility of adopting at month $x$. Since the optimal choice of $x_{i}$ decreases in the usage utility and $\eta_{i}$, we can obtain a lower bound of $x_{i}$ by using the upper bound of both quantities:

$$
\mathbb{E}_{t} U_{i}^{x}\left(\mathbf{p}, \mathbf{z}, \boldsymbol{x}_{G_{i}}\right) \leq \mathbb{E}_{t} \bar{U}_{i}^{x}\left(\mathbf{p}, \mathbf{z}, \gamma^{e q}\right)=\delta^{x}\left[\sum_{s \geq x}^{\infty} \delta^{s-x} \mathbb{E} u_{i}^{\text {approx }}\left(\mathbf{p}_{s}, \gamma_{s}^{e q}, \mathbf{z}_{t}\right)-\mathbb{E}_{t} p_{x}^{\text {handset }}+\overline{\bar{\eta}}_{i}\right]
$$

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

$$
\underline{\mathrm{x}}_{i}\left(\mathbf{p}, \mathbf{z}, \boldsymbol{\gamma}^{e q}\right)=\min _{x_{i}} \text { s.t. }\left[\mathbb{E}_{x_{i}} \bar{U}_{i}^{x_{i}}\left(\mathbf{p}, \mathbf{z}, \boldsymbol{\gamma}^{e q}\right) \geq \max _{s>x_{i}} \mathbb{E}_{x_{i}} \bar{U}_{i}^{s}\left(\mathbf{p}, \mathbf{z}, \boldsymbol{\gamma}^{e q}\right)\right]
$$

[^13]Then $\gamma_{t}^{e q}=\sum w_{i} \cdot 1\left(\underline{\mathrm{x}}_{i}\left(\mathbf{p}, \gamma^{e q}\right) \leq t\right)$, where $w_{i}$ represents the population weight of each individual. ${ }^{25}$ To find an upper bound on the dark network's behavior, I solve for equilibrium adoption by starting with an optimistic candidate adoption path ( $\left.\gamma^{0}=\max \gamma^{\text {baseline }}\right)$ and iterating each individual's adoption decision until the process converges to $\gamma^{e q}$.

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

Figure S3 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 calling prices were $20 \%$ of the baseline price path, the first adoptions of the dark network would be in 2009; if handset prices were $20 \%$ of the baseline series, the first adoptions would be in 2005 .

I then set $\tilde{T}^{\text {structural }}(\mathbf{p}, \mathbf{z})$ to the last month before the first predicted adoptions of the dark network under counterfactual prices $\mathbf{p}$ and rollout plan $\mathbf{z}$. Since I consider counterfactuals that weakly decrease coverage, I compute bounds under the baseline path of coverage. Then, the bounds on $\tilde{T}$ are similar for the range of prices above $0.2 \cdot \mathbf{p}^{\text {base }} ;$ I use that bound for all results. Under the assumptions in this section, dark nodes and links to dark nodes will not affect results prior to $\tilde{T}^{\text {structural }}(\mathbf{p}, \mathbf{z}) .{ }^{26}$

## S6. Simulation Algorithms

The simulation algorithm can be described in three nested steps. For baseline simulations, operator choices are held fixed at $a=I$. For conciseness let $\neg a=\left\{\begin{array}{ll}I & a=E \\ E & a=I\end{array}\right.$.

## Adoption Iterated Best Response Algorithm.

[^14]Figure S3. 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.

Require: firm price paths $\mathbf{p}$ and rollout plans $\mathbf{z}$
Require: candidate adoption path $\mathbf{x}^{0}$ and operator to favor $\mathbf{a}^{0}$
$k \leftarrow 0$
repeat $\triangleright$ Determine optimal adoption dates given beliefs about operator choices $\mathbf{a}(\cdot)$
for each individual $i$ do
for proposed adoption month $t=0$ to $\bar{T}$ do
for first operator $a=I$ to $E$ do
find optimal switch point $\tilde{t}$, or if not optimal to switch, $\tilde{t} \leftarrow \bar{T}$
$\mathbf{a}_{a}^{*} \leftarrow[\underbrace{\left.\begin{array}{lllll}\begin{array}{lll} & a & \cdots\end{array} a & \underbrace{(\neg a)}_{\bar{T}-\tilde{t} \text { elements }} \quad(\neg a) & \cdots & (\neg a)\end{array}\right]}_{\tilde{t} \text { elements }}$
solve $t_{a}^{*} \leftarrow \arg \max _{s} E_{t} U_{i}^{\mathbf{a}_{a}^{*}, s}\left(\hat{\mathbf{a}}_{G_{i}}, \mathbf{x}_{G_{i}}^{k}\right)$

$$
u_{a}^{*} \leftarrow E_{t} U_{i}^{\mathbf{a}_{a}^{\mathbf{a}_{a}}, t_{a}^{*}}\left(\hat{\mathbf{a}}_{G_{i}}, \mathbf{x}_{G_{i}}^{k}\right)
$$

end for
$a^{*} \leftarrow \arg \max _{a} u_{a}^{*}$
if $t=t_{a^{*}}^{*}$ then
$x_{i}^{k+1} \leftarrow t$
break
end if
end for
end for

## Equilibrium (First Mover Entrant).

Require: interconnection terms $\mathbf{f}$
Require: lower ( $\mathbf{x}^{0} \leftarrow \bar{T}$ ) or upper ( $\mathbf{x}^{0} \leftarrow 0$ ) adoption equilibrium
Require: operator to favor $\mathbf{a}^{0} \in\{I, E\}$
$\mathbf{p}_{E}, \mathbf{z}_{E} \leftarrow \arg \max _{\mathbf{p}_{E} \in\{0.1 \cdot n \mid n \in 1 \ldots 10\} \cdot \mathbf{p}^{\text {base }}, \mathbf{z}_{E}=\mathbf{z}_{(0 \%)}} \pi_{E}\left(\left\{\mathbf{p}_{I}, \mathbf{p}_{E}\right\},\left\{\mathbf{z}_{I}, \boldsymbol{z}_{E}\right\}, \mathbf{x}, \mathbf{a}, \boldsymbol{f}\right)$
s.t. $\mathbf{p}_{I}, \mathbf{z}_{I} \leftarrow \arg \max _{\mathbf{p}_{I} \in\{0.1 \cdot n \mid n \in 1 \ldots 10\} \cdot \mathbf{p}^{\text {base }}, \mathbf{z}_{I} \in\left\{\mathbf{z}_{(100 \%)}, \mathbf{z}_{(50 \%)}\right\}} \pi_{I}\left(\left\{\mathbf{p}_{I}, \mathbf{p}_{E}\right\},\left\{\mathbf{z}_{I}, \boldsymbol{z}_{E}\right\}, \mathbf{x}, \mathbf{a}, \boldsymbol{f}\right)$

3: s.t. $\mathbf{x}, \mathbf{a}$ are a network adoption partial equilibrium given firm price paths $\mathbf{p}$ and rollout plans $\mathbf{z}$, given equilibrium indexed by $\mathbf{x}^{0}$ and $\mathbf{a}^{0}$
return firm price paths $\mathbf{p}$ and rollout plans $\mathbf{z}$, and consumer equilibrium path $\mathbf{x}$ and operators a

## S7. Validation of Cost Estimates

I here test how the monopolist would behave given the supply side in the paper, using the cost estimates from Section 5. I simulate demand under the monopoly model for different

Table S6. Validation of Cost Estimates

| Price | Monopoly Profit $(\$ \mathrm{~m})$ |
| :---: | :---: |
| $1.20 \cdot \mathbf{p}^{\text {base }}$ | $121.19,131.32$ |
| $1.10 \cdot \mathbf{p}^{\text {base }}$ | $120.52,136.30$ |
| $1.00 \cdot \mathbf{p}^{\text {base }}$ | $121.89,140.00$ |
| $0.90 \cdot \mathbf{p}^{\text {base }}$ | $121.88,139.50$ |
| $0.80 \cdot \mathbf{p}^{\text {base }}$ | $120.00,136.59$ |

Cells represents profit earned by monopoly, in low and high equilibrium through $T$.
multiples of the baseline price path. Results are shown in Table S6: given these costs, the baseline price path maximizes profits. This suggests the monopoly demand and supply models are consistent.

## Part 3. Robustness

For most robustness tests I replicate the equivalent of Figure 4 from the paper, which shows price, consumer surplus, profits, and government revenue as a function of the interconnection rate (including the focal rate of $\$ 0.11 /$ minute denoted by a dotted line).

The incumbent's investment decision itself $\left(\mathbf{z}^{I} \in \mathbf{z}_{(100 \%)}, \mathbf{z}_{(50 \%)}\right)$ is lumpy, and in nearly all counterfactuals the incumbent would opt to build all towers $\left(\mathbf{z}_{(100 \%)}\right)$. I focus instead on ROI, which is a more responsive measure of investment. For simpler interpretation, I report prices, profits, welfare, and government revenue under equilibria where the incumbent is constrained to build the full set of towers. I report the ROI of building the rural towers covering the lowest $50 \%$ of population as described in the main text. If that ROI is below zero, that is an indication that in equilibrium the firm may wish to deviate to omit low population towers $\left(\mathbf{z}_{(50 \%)}\right)$.

## S8. Alternate Investment Cutoffs

The main paper explores incentives to build the half of rural towers covering the lowest population areas. That compares profits under a full rollout $\left(\mathbf{z}_{(100 \%)}\right)$ against one where those towers are not built $\left(\mathbf{z}_{(50 \%)}\right)$, in a full equilibrium with prices. Although it is computationally costly to compute full equilibria for a larger set of rollout cutoffs, in this section I hold fixed equilibrium prices from the full rollout $\left(\mathbf{z}_{(100 \%)}\right)$ and consider unilateral incentives to deviate for a larger menu of cutoffs.

Figure S4a considers incentives under the baseline scenario, and under competition with the focal interconnection rate of $\$ 0.11 / \mathrm{min}$. I report the ROI of building tower $\mathbf{z}_{(100 \%)}$, from a baseline of $\mathbf{z}_{(0 \%)}, \mathbf{z}_{(25 \%)}, \mathbf{z}_{(50 \%)}$, and $\mathbf{z}_{(75 \%)}$. In each case, the returns are higher under competition for this interconnection rate.

Björkegren (2019) finds that roughly $11 \%$ of the towers active by 2009 were not profitable for the monopolist to build, and infers that these were built as a result of coverage obligations. That paper ranks towers by an alternate metric, the observed baseline revenue earned by that tower, which is highly correlated with population (see Section S4.1). Figure S4b finds that this set of 10 towers that were unprofitable in the baseline scenario would have been profitable under competition, suggesting that they would be built even without government intervention.

## S9. Different Random Preference Draws

In my survey of Rwandan mobile phone consumers, I find that idiosyncratic preferences for each operator are slight: consumers mostly care about prices and coverage. I estimate a mean difference in idiosyncratic preference $m\left(\eta_{i}^{I}-\eta_{i}^{E}\right)=\$ 2.45$ ( $=\$ 0.01$ per month), and standard deviation $\sigma\left(\eta_{i}^{I}-\eta_{i}^{E}\right)=\$ 6.72$. To reduce the computational burden of my simulations, my main results report equilibria given a single draw from a Normal distribution with these parameters: $\Delta \eta_{i s} \stackrel{i i d}{\sim} N\left[m\left(\eta_{i}^{I}-\eta_{i}^{E}\right), \sigma\left(\eta_{i}^{I}-\eta_{i}^{E}\right)\right]$. As a robustness test, I impose two potential operator choices and assess the how much adoption equilibrium outcomes vary between different preference draws. Table S 7 presents these results. The standard deviation of outcomes across draws is very small, suggesting that the particular draw of idiosyncratic preferences has very little impact on outcomes.

Figure S4. ROI under Alternate Investment Cutoffs (a) Ranking by population

$\rightarrow$ Competition: interconnect $\$ 0.11$ - Monopoly - high low
(b) Ranking by baseline revenue (as in Björkegren (2019))

$\rightarrow$ Competition: interconnect $\$ 0.11-$ Monopoly $\quad$ high low

Outcomes computed from January 2005 through horizon December 2008, for unilateral deviations from the equilibrium under the focal interconnection rate. Filled marks denote high equilibrium and open marks denote low equilibrium. Equilibrium with entrant moving first, and consumers favoring incumbent. In panel (a), towers ranked by population; in panel (b), ranked by baseline revenue.

Table S7. Robustness: Draws of Idiosyncratic Preferences for Entrant Operator Choices (Imposed)

| Prices | Entrant$\frac{\mathbf{p}^{E}}{\mathbf{p}^{\text {base }}}$ | Incumbent <br> Coverage $\mathbf{z}^{I}$ |  | Consumer | Subscriber Rev | nue | Gov. | Number of |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Incumbent $\frac{\mathbf{p}^{I}}{\mathbf{p}^{\text {base }}}$ |  |  |  | Surplus $\$ \mathrm{~m}$ | Incumbent $\$ \mathrm{~m}$ | Entrant <br> \$m | Revenue <br> \$m | Draws <br> $\Delta \eta_{i s}$ |
| 1.00, 1.00 | 1.00, 1.00 | $\mathbf{Z}_{(100 \%)}$ | Mean | 243.46, 269.60 | 164.97, 187.21 | 0.09, 0.10 | 65.30, 73.05 | 3 |
|  |  |  | SD | 0.04, 0.06 | 0.01, 0.02 | 0.001, 0.001 | 0.002, 0.005 | 3 |
| 0.70, 0.60 | 0.60, 0.50 | $\mathbf{z}_{(0 \%)}$ | Mean | 366.18, 454.14 | 149.23, 140.89 | 18.36, 37.11 | 67.41, 72.39 | 3 |
|  |  |  | SD | 0.07, 0.07 | 0.01, 0.002 | 0.01, 0.01 | 0.002, 0.001 | 3 |

Table shows network partial adoption equilibria conditioned on the given prices and coverage, for the given

## S10. Different Horizons

Results under different horizons could differ for two reasons. First, firms may take different actions when their actions span different horizons. Second, under long enough horizons and low enough prices, dark portions of the network that are not observed in my data may become active. If those dark portions became active, I may mischaracterize the actions that firms would take.

The main text reports results over a horizon that would not be affected by the omission of dark nodes for prices as low as $20 \%$ of the baseline price path, under the model of the dark network developed in Section S5 ( $\tilde{T}^{\text {structural }}\left(0.2 \cdot \mathbf{p}^{\text {base }}, \mathbf{z}\right)$ ). This section computes the main simulation figures from the paper using different horizons.

First, I assess a longer horizon through the end of the data $T=$ May 2009 in Figure S5. Results are similar to the main results reported in the paper. Adding a competitor improves welfare substantially through horizon $T$.

Second, I consider an even longer horizon to account for the possibility that the firm may make an investment in this period anticipating a payoff in the future. I compute discounted profits through $T=$ May 2009, and add to that the discounted profits of that final period repeated for 3 years. This would allow firms to invest during early periods in order to earn profits at $T$. I report profits through this time period including repetition, but other outcomes (consumer surplus and government revenue) only through the end period of data, T. Results are shown in Figure S6. Under high interconnection rates, the results are similar to the main results, though under the focal policy, competition does not lower prices as much, and welfare is not as high. However under this horizon, incentives to invest continue to be higher than baseline even under lower interconnection rates ( $\$ 0.05-\$ 0.10$ per minute). Under those lower interconnection rates, prices are lower, and welfare is increased substantially. Under interconnection rates near zero, the grid of price options is too coarse to maintain numeric stability. Because the last period is repeated over 3 years, this horizon magnifies small differences. It appears that both equilibrium prices and investment ROI rise near an interconnection rate of zero, though this may be an artifact of the coarseness of the grid.

Both of these longer horizons will omit the response of nodes in the dark network.

Figure S5. Market Outcomes as Function of Competition Policy (through horizon $T=$ May 2009; First Mover: Entrant, Incumbent-Favoring)

$75 \%$
$\overline{\mathrm{O}} 50 \%$
¢
$25 \%$
$0 \%$
Additional Competitor
Holding Rollout Plans Fixed





The left column shows outcomes under the baseline scenario; and the right column when an additional competitor is granted a license at month $t=0$ under different interconnection rates (shown decreasing with the x-axis). Outcomes computed from January 2005 through horizon May 2009. Dotted line denotes a focal interconnection rate that balances competitive pressure with incentives to invest. Filled marks denote high equilibrium and open marks denote low equilibrium. Equilibrium with entrant moving first, and consumers favoring incumbent.

I also assess equilibrium prices under a shorter, more conservative horizon, up to December $2005=\tilde{T}^{\text {conservative }}\left(0.3 \cdot \mathbf{p}^{\text {base }}, \mathbf{z}\right)$. Up to this period, for prices as low as $0.3 \cdot \mathbf{p}^{\text {base }}$, the dark network would face conditions strictly no more attractive than in my data (as

Figure S6. Market Outcomes as Function of Competition Policy (through horizon $T=$ May 2009, with firms maximizing profits anticipating that the end period will be repeated for three years; First Mover: Entrant, IncumbentFavoring)

| ¢ 1.00 |  |
| :---: | :---: |
| ${ }^{\circ}$ | 0.75 |
| 응 0.50 |  |
| - | 0.25 |
| O | 0.00 |

$250 \%$
$200 \%$
$\overline{\mathrm{O}} 150 \%$
$\mathbf{~ 1 0 0 \%}$
$50 \%$
$0 \%$


Additional Competitor
Holding Rollout Plans Fixed


$\rightarrow$ C Surplus $\boldsymbol{-} \boldsymbol{-}$ Gov Revenue $-\boldsymbol{-}$ Profit Entrant $\boldsymbol{-}$ - Profit Incumbent high low


Consumer surplus and government revenue are reported through $T$. Profits are reported through $T$ plus with period $T$ repeated three years.

The left column shows outcomes under the baseline scenario; and the right column when an additional competitor is granted a license at month $t=0$ under different interconnection rates (shown decreasing with the x-axis). Outcomes computed from January 2005 through horizon May 2009, except for profits where the last month is repeated for three years. Dotted line denotes a focal interconnection rate that balances competitive pressure with incentives to invest. Filled marks denote high equilibrium and open marks denote low equilibrium. Equilibrium with entrant moving first, and consumers favoring incumbent.

Figure S7. Market Outcomes as Function of Competition Policy (through horizon $\tilde{T}^{\text {conservative }}\left(0.3 \cdot \mathbf{p}^{\text {base }}, \mathbf{z}\right)=$ December 2005; First Mover: Entrant, Incumbent-Favoring)


The left column shows outcomes under the baseline scenario; and the right column when an additional competitor is granted a license at month $t=0$ under different interconnection rates (shown decreasing with the x-axis). Outcomes computed from January 2005 through horizon December 2005. Dotted line denotes a focal interconnection rate that balances competitive pressure with incentives to invest. Filled marks denote high equilibrium and open marks denote low equilibrium. Equilibrium with entrant moving first, and consumers favoring incumbent.
described in Section S5, this horizon requires fewer assumptions but is a looser bound). See results in Figure S7. Competition lower prices even more than the baseline case, and results in substantial welfare gains, though there are numerical instabilities for the grid of price options. ${ }^{27}$ This conservative time horizon covers the construction of few rural towers, so is not well suited to answering questions about investment.

[^15]Under all horizons, outcomes are similar: competition results in dramatically lower prices and increases welfare substantially. Competition has mixed effects on incentives to invest in general, but increases incentives under the focal interconnection rate.

## S11. Alternate Consumer Beliefs

In my main model, at the point where consumer $i$ selects adoption date $x_{i}$, he knows the adoption dates $x_{j}$ of each contact and has beliefs $\hat{\mathbf{a}}_{j}(\mathbf{p}, \mathbf{z})$ about their operator choices. Those beliefs depend on underlying factors but not the actual operator choices that his contacts coordinate on. After $i$ finalizes his adoption decision $x_{i}$, he then may select his own operator choice $\mathbf{a}_{i}$ knowing the actual operator choices of his contacts, $\mathbf{a}_{j}$. Under this two step model, equilibria have a two dimensional lattice structure, in adoption (low e or high $\bar{e}$ ) and operator favor (coordination favoring the incumbent $e^{I}$ or entrant $e^{E}$ ). The paper report outcomes for equilibria that favor the incumbent ( $\bar{e}^{I}$ and $\underline{e}^{I}$ ). This section considers alternate beliefs.

S11.1. Entrant-Favoring Equilibria. Results under the corresponding equilibria that favor the entrant ( $\bar{e}^{E}$ and $\underline{\mathrm{e}}^{E}$ ) are presented in Figure S 8 (with corresponding normal form game boards in Tables S18 and S19 for the focal interconnection rate). Differences are minor. ${ }^{28}$

Because subscribers pay the same price for on- and off-network calls, the only reason why a subscriber's operator choice affects his contact's is that their coverage is complementary: if my contact switches to an operator with better coverage, that increases my value of having better coverage. As a result, whether adoption is low or high is quantitatively important, but whether individual beliefs favor the incumbent or entrant is minor.

S11.2. Correctly Anticipating Contacts' Operator Choices. If instead, consumers know which operators their contacts are coordinating on at the point of adoption ( $\hat{\mathbf{a}}_{j} \equiv \mathbf{a}_{j}$ ), the structure bends away from a lattice. $j$ 's choice of operator affects both his adoption date $\left(x_{j}\right)$ and coverage $\left(\phi_{j t}\left(\mathbf{z}^{a_{j}}\right)\right)$, 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

[^16]Figure S8. Market Outcomes as Function of Competition Policy (First
Mover: Entrant, Entrant-Favoring)
Baseline Scenario Additional Competitor


Holding Rollout Plans Fixed





The left column shows outcomes under the baseline scenario; and the right column when an additional competitor is granted a license at month $t=0$ under different interconnection rates (shown decreasing with the x-axis). Outcomes computed from January 2005 through horizon December 2008. Dotted line denotes a focal interconnection rate that balances competitive pressure with incentives to invest. Filled marks denote high equilibrium and open marks denote low equilibrium.
coverage; this may make the network more desirable for some contacts and less desirable for others.

In this setting, consumer adoption may not reach equilibrium. As a robustness exercise, I compute approximate equilibrium bounds for this case with a two step method. First, I compute the upper (lower) envelope equilibrium that would result from combining the most (least) attractive envelope of coverage and prices offered by the two firms, which is monotonic and represents an upper (lower) bound on all equilibria. Second, I start from that envelope to compute the adoption equilibrium in the actual prices and coverage. 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. ${ }^{29}$

Results from these approximate equilibria are presented in Figure S9 (with corresponding normal form game boards in Tables S20 and S21 for the focal interconnection rate). Differences with the main results are minor, which is consistent with any deviation of consumer beliefs $\hat{\mathbf{a}}_{j}(\mathbf{p}, \mathbf{z})$ from contacts' actual choices having minor effects on results.

[^17]Figure S9. Market Outcomes as Function of Competition Policy (First
Mover: Entrant, Correct Operator Beliefs During Adoption)


The left column shows outcomes under the baseline scenario; and the right column when an additional competitor is granted a license at month $t=0$ under different interconnection rates (shown decreasing with the x-axis). Outcomes computed from January 2005 through horizon December 2008. Dotted line denotes a focal interconnection rate that balances competitive pressure with incentives to invest. Filled marks denote high equilibrium and open marks denote low equilibrium.

## S12. First Mover

The main paper reports results where the regulator asks the entrant to make its choices first, followed by the incumbent. This section reports results when the regulator asks the firms to make decisions in different orders. First, reverse order: first the incumbent selects prices and a rollout plan, and it is followed by the entrant selecting prices. Then, simultaneously. This can also be inspected in the normal form game boards presented in Section S15 (the boards are identical regardless of the order; the order just changes the outcome that is selected along each board).

Incumbent First. Results are presented in Figure S10. The price decisions are less stable on the grid than in the main results, where the entrant moves first (including two points where the firms select identical prices). The ROI results are also less stable; they are less informative in the case where the incumbent makes the first move because they are computed holding fixed the entrant's action (which in this structure could have responded to the incumbent's action). ${ }^{30}$

[^18]Figure S10. Market Outcomes as Function of Competition Policy (First Mover: Incumbent, Incumbent-Favoring)

## 

$200 \%$
$150 \%$
〇〇 $100 \%$
$\boxed{\square} \quad \square$
$50 \%$
$0 \%$



The left column shows outcomes under the baseline scenario; and the right column when an additional competitor is granted a license at month $t=0$ under different interconnection rates (shown decreasing with the x-axis). Outcomes computed from January 2005 through horizon December 2008. Dotted line denotes a focal interconnection rate that balances competitive pressure with incentives to invest. Filled marks denote high equilibrium and open marks denote low equilibrium.

Simultaneous Moves. Next I consider the case where firms make simultaneous choices. Best responses can sometimes cycle locally around a small neighborhood, so I report $\varepsilon$ equilibria:

Given consumer types $\boldsymbol{\eta}$, interconnection terms $\boldsymbol{f}$, and horizon $\tilde{T}$, an $\varepsilon$-equilibrium of index $e$ is $\left(\mathbf{p}^{I}, \mathbf{p}^{E}, \mathbf{z}^{I}, \mathbf{z}^{E}, \mathbf{x}, \mathbf{a}, \mathbf{d}\right)$ such that each firm $F$ cannot profit more than $\varepsilon$ by deviating from price sequence $\mathbf{p}^{F}$ and tower construction plan $\mathbf{z}^{F}$, given the competing firm's price sequence and tower construction plan, and interconnection terms:
$\pi_{F}^{\tilde{T}}(\mathbf{p}, \mathbf{z}, \mathbf{x}(\mathbf{p}, \mathbf{z}, \boldsymbol{\eta}, e), \mathbf{a}(\mathbf{p}, \mathbf{z}, \boldsymbol{\eta}, e), f) \geq \pi_{F}^{\tilde{T}}(\tilde{\mathbf{p}}, \tilde{\mathbf{z}}, \mathbf{x}(\tilde{\mathbf{p}}, \tilde{\mathbf{z}}, \boldsymbol{\eta}, e), \mathbf{a}(\tilde{\mathbf{p}}, \tilde{\mathbf{z}}, \boldsymbol{\eta}, e), f)-\varepsilon$ for all $\tilde{\mathbf{p}}^{F}$ and $\tilde{\mathbf{z}}^{F}$
where $\mathbf{p}=\left[\mathbf{p}^{I}, \mathbf{p}^{E}\right], \mathbf{z}=\left[\mathbf{z}^{I}, \mathbf{z}^{E}\right]$ and $\tilde{\mathbf{p}}=\left\{\begin{array}{ll}{\left[\tilde{\mathbf{p}}^{I}, \mathbf{p}^{E}\right]} & F=I \\ {\left[\mathbf{p}^{I}, \tilde{\mathbf{p}}^{E}\right]} & F=E\end{array}, \tilde{\mathbf{z}}=\left\{\begin{array}{ll}{\left[\tilde{\mathbf{z}}^{I}, \mathbf{z}^{E}\right]} & F=I \\ {\left[\mathbf{z}^{I}, \tilde{\mathbf{z}}^{E}\right]} & F=E\end{array}\right.\right.$. Consumers' adoption dates $\mathbf{x}(\mathbf{p}, \mathbf{z}, \boldsymbol{\eta}, e)$, operator choices $\mathbf{a}(\mathbf{p}, \mathbf{z}, \boldsymbol{\eta}, e)$, and calling decisions d represent an adoption equilibrium of index $e$.

To discover an $\varepsilon$-equilibrum, I start at full rollout and baseline prices, and allow 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 through $\tilde{T}$, anticipating how consumers will adopt and use phones. I terminate the algorithm once neither firm would profit more than $\varepsilon=\$ 2 m$ by deviating. If the algorithm discovers multiple $\varepsilon$-equilibria, I report the one for which any profitable deviation is smallest. Not all parameters lead to an $\varepsilon$-equilibrium. Results are reported in Figure S11. ${ }^{31}$

[^19]Figure S11. Market Outcomes as Function of Competition Policy (Simultaneous Move, Incumbent-Favoring)


The left column shows outcomes under the baseline scenario; and the right column when an additional competitor is granted a license at month $t=0$ under different interconnection rates (shown decreasing with the x-axis). Outcomes computed from January 2005 through horizon December 2008. Dotted line denotes a focal interconnection rate that balances competitive pressure with incentives to invest. Filled marks denote high equilibrium and open marks denote low equilibrium. Only interconnection rates that lead to $\varepsilon$-equilibria are shown, for $\varepsilon=\$ 2 m$.

## S13. Simpler Demand Models

Independent consumer decisions (fixed beliefs). Nonnetwork models commonly treat individual decisions as independent, either explicitly or implicitly, by aggregating demand. I assess a modified equilibrium where each individual makes their decisions independently, ruling out ripple effects. Individuals make decisions independently, believing that others will adopt at the same month as under baseline, using the operator $\hat{\mathbf{a}}_{j}(\mathbf{p}, \mathbf{z})$ that is optimal for calls to the median individual from their location.

Figure S12 presents full equilibrium results for this model. By neglecting how one node's decision affects the decision of others in the network, such a model incorrectly suggests that incumbent prices will remain high under competition (85-100\% of baseline price path), and that welfare effects are much lower. Under this naive model, competition would induce the incumbent to lower prices only $1 / 3(1 / 2)$ as far as it does under a full equilibrium, for the focal interconnection rate. This model also omits $20 \%$ (13\%) of the welfare gains from competition.

I also assess impact on incentives to invest, by imposing the equilibrium prices from the full model and then computing adoption equilibria. The simpler model would suggest the incumbent's subscriber revenue from building rural towers are $52 \%$ ( $56 \%$ ) too small and the ROI $54 \%$ (55\%) too small.

For this reason, all main results include the full model with network ripple effects.
Stochastic links from a simple distribution. An alternate simplification would allow for ripple effects, but consider categories of links rather than the actual structure of the network (e.g., Ryan and Tucker, 2012). I create a rewired graph $G^{\prime}$ by replacing each link $i j$ with link $i j^{\prime}$, with the same communication intensity (shock distributions $F_{i j^{\prime}}=F_{i j}$ ), but where $j^{\prime}$ is randomly selected from the set of nodes with the same baseline adoption date and final coverage as $j$ (e.g., equally remote). $G$ and $G^{\prime}$ appear identical under representations that only consider patterns of links: individual $i$ is linked to the same number of similar nodes, with the same corresponding link intensities. But $G^{\prime}$ jumbles the structures in the network. When equilibrium prices from the full model are imposed, this rewired network would result in the incumbent's subscriber revenue from building rural towers being $86 \%$ too large and ROI $17 \%$ too large, in the low equilibrium.

Figure S12. Market Outcomes as Function of Competition Policy (No Ripple Effects)


The left column shows outcomes under the baseline scenario; and the right column when an additional competitor is granted a license at month $t=0$ under different interconnection rates (shown decreasing with the x-axis). Outcomes computed from January 2005 through horizon December 2008. Dotted line denotes a focal interconnection rate that balances competitive pressure with incentives to invest. Filled marks denote high equilibrium and open marks denote low equilibrium. Equilibrium with entrant moving first, and consumers favoring incumbent.

Table S8. Benchmark Monopoly Simulations (million \$, 2005-5.2009)

|  | Consumer <br> Surplus | Gov. <br> Revenue | Firm <br> Profits |  | m Reven By Co | e Breakd <br> nection |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | All links | All links | All links | Rural- <br> Rural | Rural- <br> Urban | Urban- <br> Rural | Urban- <br> Urban |
| Baseline | [244, 270] | [65, 73] | [122, 140] | [30, 33] | [17, 18] | [24, 28] | [95, 108] |
| Impact: |  |  |  |  |  |  |  |
| Charge eventual competitive price | $+330,+338$ | -2, -4 | -51, -62 | -4, -5 | -4, -5 | -1, -4 | -11, -18 |
| ... only proximal effect | $+288,+316$ | -7, -9 | -58, -67 | -5, -6 | -5, -6 | -3, -5 | -18, -22 |
| ... additional ripple effects | $+42,+22$ | $+5,+4$ | +7, +5 | $+2,+2$ | +1, +1 | $+2,+1$ | $+7,+4$ |
| No rural expansion | -81, -92 | -11, -14 | -19, -27 | -9, -10 | -4, -4 | -6. -8 | -14, -20 |
| ... only proximal effect | -77, -83 | -10, -11 | -17, -21 | -8, -9 | -4, -4 | -6, -7 | -12, -15 |
| ... additional ripple effects | -3, -8 | -1, -2 | -2, -6 | -0, -1 | -0, -0 | -0, -1 | -1, -5 |

Baseline reported for the lower bound and upper bound estimate of the equilibrium. Impacts represent the difference in these bounds between the counterfactual simulation and the baseline. Utility and revenue reported in 2005 U.S. Dollars, discounted at a rate of $\delta$. Consumer surplus includes the surplus utility each individual receives from the call model through May 2009, minus the cost of holding a handset from the time of adoption until May 2009. Firm revenue is broken down by the type of link it derives from.

## S14. Monopoly Benchmarks

To gauge the source of welfare benefits, I simulate the effect of price and coverage changes under the benchmark where the incumbent acts as a monopolist (where operator C is not granted a license, and as elsewhere the unmodeled operator B and its subscribers are held fixed). I hold fixed individuals' operator choices ( $a_{i t} \equiv I$ ), and trace the impact of prices on welfare, and how the revenue from building rural towers is distributed across the network. I report results under the full horizon of the data (January 2005-May 2009, so $\tilde{T}=T$ ). I refer to lower equilibrium outcomes in the main text (and place upper equilibrium outcomes in parentheses, or omit if identical).

Results are shown in Table S8. At baseline, the incumbent's mobile phone system provides net social welfare of $\$ 431 \mathrm{~m}$ ( $\$ 483 \mathrm{~m}$ ) over this period, an amount equivalent to $3 \%$ of Rwandan GDP over the same period.

Lowering prices has large welfare benefits. I simulate the equilibria that would result if the incumbent were to lower its price to what it charged after Operator C entered in 2010: an immediate drop in calling prices of $77 \%$. I assume the firm expands coverage as in the baseline. I first allow each individual to reoptimize their choices individually, without allowing those changes to ripple through the network ('only proximal effect'). I then allow all
nodes to adjust their decisions until a new equilibrium is reached ('additional ripple effects') which capture network effects as the impact of these decisions ripple though the network. These effects are not captured in aggregate demand functions. I also report the total effect.

As shown in Table S 8 row 2, the total effect of this price reduction would have reduced firm profits, but more than doubled the surplus accruing to consumers. On net, social welfare would have increased by $\$ 277 \mathrm{~m}$ ( $\$ 272 \mathrm{~m}$ ), which corresponds with $1.6-1.7 \%$ of GDP or $8-9 \%$ of official development aid over this time period. ${ }^{32}$ Network ripple effects account for $24 \%$ $(21 \%)$ of the revenue change and $19 \%(11 \%)$ of the welfare increase (as shown in rows $2-4)$, suggesting that aggregate demand functions will misstate the effects of price changes in this industry.

Investment in rural towers generates network spillovers. Because competition splits networks, i would cause firms to internalize only a fraction of potential network effects from an investment. I gauge these potential network effects in the benchmark model by simulating building full baseline coverage $\left(\mathbf{z}^{I}=\mathbf{z}_{(100 \%)}\right)$ relative to a counterfactual where the incumbent builds only urban towers $\left(\mathbf{z}^{I}=\mathbf{z}_{(0 \%)}\right)$. I impose the relevant rollout plan, compute corresponding coverage, 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 the full rural expansion, holding prices fixed at the baseline price path. As shown in Table S 8 row 5, rural-rural links generated only $28 \%(24 \%)$ of the additional revenue from building rural towers. $31 \%$ ( $29 \%$ ) came from links between rural and urban areas. Nearly half- $44 \%$ (48\%) -came from increased urban-urban calling:

- $92 \%(75 \%)$ of urban-urban revenue comes from proximal effects (row 6): some urban consumers make calls from rural areas and thus directly benefit from rural coverage (which is included in their coverage measure $\phi_{i t}\left(\mathbf{z}^{a}\right)$ ).
- $8 \%(25 \%)$ of urban-urban revenue comes from network spillover effects (row 7), which can result from even consumers who have no desire to call or use rural coverage. These benefits accrue to the interior of the urban network, so would only partially be internalized if that network were split.

[^20]These benchmarks suggest that competition has the potential to impact both welfare and investment.

## Part 4. Additional Reference

## S15. Normal Form Game Boards

The following tables show simulation results for a sample of interconnection rates, in the high and low equilibria. See Table S 9 for an index to the game boards. I omit computing most of the upper triangular portion of the matrix, which corresponds to the entrant charging higher prices than the incumbent despite having worse coverage: those cells tend to be dominated for the entrant because the vast majority of consumers subscribe to the incumbent. (This is the case except for high prices and high interconnection rates, for which I compute these cells.) The 'last 34 rural towers' represent the half of rural towers covering the lowest population areas.

These tables include boldface and underlines to highlight equilibria when the entrant is the first mover.

Table S9. Index of Normal Form Game Boards

Mover Entrant Favor Incumbent


Mover Entrant Favor Incumbent


First Mover Entrant Favor Incumbent
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| 0 |  |
| :---: | :---: |
| 5 |  |
| 0 |  |
| 0 |  |
|  |  |

|r
onv
(2)



TABLE S13. Competitive Interaction: Interconnection $\$ 0.11$ Switching Cost $\$ 36$ High Equilibrium -200812 (50pct dark) First Mover Entrant Favor Incumbent
Mover Entrant Favor Incumbent


 1 $\begin{array}{ll}\theta_{0} & 0 \\ 0 & 5 \\ \vdots \\ \sigma & 0 \\ 0 & 0\end{array}$


TABLE S15. Competitive Interaction: Interconnection $\$ 0$ Switching Cost $\$ 36$ High Equilibrium -200812 (50pct dark) First Mover Entrant Favor Incumbent


First Mover Entrant Favor Entrant


 actions in rows; e
nses are bolded. U Fince Si9. Competitive Interact






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[^1]:    ${ }^{2}$ Although the maximum technical range of a GSM tower is 35 km , the range in practical use tends to be smaller.
    ${ }^{3}$ This allows them their own phone number and balance, but it is difficult to receive calls. A representative survey found that fewer than $1 \%$ of individuals in 2007 owned SIMs without handsets (Stork and Stork, 2008), and within the phone data on average there are actually $3 \%$ more handsets than accounts active in a given month.

[^2]:    ${ }^{4}$ This pattern would include the use of payphones that run on the mobile network, which I omit from this analysis. Payphones place approximately $12 \%$ of call durations but receive only $0.8 \%$. Because payphones receive so few outgoing calls from the rest of the network, omitting them would have little effect on the preferred usage model which uses outgoing calls.
    ${ }^{5}$ This omits the top $1 \%$ of texters who text heavily.

[^3]:    ${ }^{6}$ While there is evidence that the poor in developing countries have high returns to capital, which suggest that costs of borrowing may be high for consumers (Udry and Anagol, 2006; De Mel et al., 2008), the resulting implications for time preference can be unclear (Dean and Sautmann, 2014). Consumers adopting phones during this period were relatively wealthy. If I imposed different discount rates for firms and consumers, firms would endogenously change their offerings to exploit this difference in time preference, for example, twisting the time path of their choices to extend credit that is collected through higher use fees in the future. This behavior is not observed in these markets.

[^4]:    ${ }^{7}$ I omit three respondents who reported extreme idiosyncratic preferences for one of the operators ( 100 x the modal response of $+/-1000 \mathrm{RwF}$. 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.
    ${ }^{8}$ 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.
    ${ }^{9}$ Calls under the 'per minute' plan were billed by the first minute, and then 30 second increments.

[^5]:    ${ }^{10}$ Standard errors computed with 1,000 bootstrap draws.
    ${ }^{11}$ The model itself is encoded as an Excel workbook with 18 worksheets and is described in a 168 page writeup.
    ${ }^{12}$ Infrastructure is specified in detail, including the cabinets, software, and batteries for different equipment.

[^6]:    ${ }^{13}$ This data is crowdsourced, and so may be missing some towers, but appears fairly complete for these countries when compared to operator coverage maps.
    ${ }^{14}$ This is less clear in Tanzania. In particular, the blue operator seems to better serve the island of Zanzibar.

[^7]:    ${ }^{15}$ With the exception that several years later once smartphones had gained popularity, Operator D specialized in data plans.
    ${ }^{16}$ The third operator saw a spike in text message volumes in late 2013; it is unclear if this spike was related to a drop in price in 2012 or some other factor.

[^8]:    ${ }^{17}$ 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. 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.

[^9]:    ${ }^{18}$ 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.
    ${ }^{19}$ Mobile C introduced a feature that plays music while a caller is waiting for the receiver to pick up.

[^10]:    ${ }^{20}$ In simulations this will also tend to make late adopting individuals a bit too sensitive to the adoption of their realized contacts, however I expect this effect to be small.

[^11]:    ${ }^{22}$ I assume that individuals that adopted before 2011 still have phones when surveyed in 2011.

[^12]:    ${ }^{23}$ Results would be similar if usage is a combination of services but prices of different services change proportionally with voice prices.

[^13]:    ${ }^{24} \gamma_{t}^{\text {baseline }}$ is derived from regulator statistics on mobile subscriptions; see Supplemental Appendix.

[^14]:    ${ }^{25}$ The total number of accounts implied by the survey data during the earlier period is less than the number present in the phone records. My results will be valid as long as in a counterfactual, any nodes omitted from the survey would not adopt prior to those in the 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.)
    ${ }^{26}$ Results may still be affected by latent links between nodes that were active at time: two adopters who did not call each other under baseline 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 $\tilde{T}^{\text {structural }}(\mathbf{p}, \mathbf{z})$, which omits these latent links, to those under $\tilde{T}^{\text {conservative }}(\mathbf{p}, \mathbf{z})$, would include the behavior of any latent links and represents a shorter time period, in the following section.

[^15]:    ${ }^{27}$ My data does not cover prices of $0.2 \cdot \mathbf{p}^{\text {base }}$ or below, so I am not able to evaluate a short enough horizon to rule out all dark network activity below that price. Note that in order to value the stock of handsets, I assume that subscribers sell back their handsets at the end period $\tilde{T}$ at the prevailing price. Because handset prices declined dramatically leading up to this end period, the computed consumer surplus appears negative in the baseline.

[^16]:    ${ }^{28}$ As shown in Figure S8, there is an inversion of the equilibrium prices at the highest interconnection rate for the upper adoption equilibrium, which results in the ROI being lower than competition at that point. This is likely to result from coarseness of the grid.

[^17]:    ${ }^{29}$ If fewer than 60 nodes are shifted for at least 10 iterations.

[^18]:    ${ }^{30}$ One could instead compute ROI allowing prices to adjust (equivalent to a total derivative). I do not do this because the scale of the price grid causes price adjustment to be lumpy. The grid scale is sufficiently fine for large policy changes like the interconnection variation, but the rural tower investment is a small policy change. As a result, changes in the incentives to build towers would get muddied with whether they trigger a price change. I hold prices fixed to avoid this issue (equivalent to a partial derivative).

[^19]:    ${ }^{31}$ There are some interconnection rates in this range that do not lead to an $\varepsilon$-equilibrium for this grid resolution and $\varepsilon \leq \$ 2 \mathrm{~m}$. I omit these from the plot.

[^20]:    ${ }^{32}$ This represents a lower bound, as results through $T$ do not include benefits to the dark network.

