



Mobile Phones and Gender Norms: Evidence from Afghanistan

Seunghun Chung¹, Robert M. Gonzalez² & Ahmad Shah Mobariz³

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Abstract

This paper examines the impact of mobile phone expansion on gender norms in Afghanistan. We combine cell tower data from the country's largest operator with nationally representative survey data on attitudes toward women's education, employment, and leadership. Using lightning strike intensity as an instrument for network expansion, we find that greater mobile access lead to more progressive views toward women's education and employment, particularly among men. Women's support for female leadership also increased while men's stated views did not change. We explore information and labor supply channels as potential mechanisms driving these effects. We find little evidence for a labor market participation channel, suggesting that information access—both direct and via networks—is more likely to explain the observed attitudinal changes. While we find no downstream effects on women's schooling or employment participation, mobile expansion increased votes for female candidates, the number of women running, and the share elected to office. These results suggest that expanding access to mobile technology can weaken restrictive gender norms even in settings with strong cultural constraints.

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Keywords

Phone Access, Culture, Gender Norms

¹ Yale University. Email: seung-hun.chung@yale.edu.

² Georgia Institute of Technology. Email: robert.gonzalez@gatech.edu.

³ University of West Georgia. Email: amobariz@westga.edu.

1 Introduction

Gender norms evolve with economic and technological change, yet they can be slow to shift in settings where social enforcement is strong. Digital communication technologies may nonetheless reshape norms by expanding exposure to new ideas and by enabling more private information acquisition and expression (Tegegn, 2024; Pearse and Connell, 2016; Bovenberg, 2002; Antonucci et al., 2017). While much of the literature focuses on the economic and political impacts of mobile technology, its role in shaping gender norms remains underexplored, particularly in highly conservative contexts.¹

This paper examines whether mobile phones can influence gender norms in a conservative society like Afghanistan. Leveraging the spatial and temporal roll-out of the largest mobile network operator in Afghanistan as a quasi-natural experiment, and employing an instrumental variable strategy that has been used and validated in previous literature, we find that increased mobile connectivity led to a decline in conservative attitudes toward women, particularly among men, while producing no detectable effects on downstream outcomes such as women’s schooling or employment. These findings suggest that while expanded access to mobile technology can catalyze shifts in norms, translating this into changes in behavioral and socioeconomic outcomes may be difficult in constrained environments.

Between 2001 and 2021, Afghanistan underwent major political, economic, and social change. After the U.S. intervention following the 9/11 attacks, the Taliban regime collapsed and a democratically elected government was established (Maley and Maley, 2002; Nixon and Ponzio, 2007). The economy grew rapidly, fueled in large part by foreign military spending and international aid (World Bank, 2022; Hassani, 2020), and women gained greater access to education and public life (Najam et al., 2024). These shifts coincided with a rapid expansion in mobile connectivity. Following the resumption of operations by Afghan Wireless Communication Company (AWCC) in

¹For example, studies have examined mobile phones and market efficiency (e.g., Aker, 2010; Abraham, 2006), agricultural outcomes (e.g., Muto and Yamano, 2009), savings (e.g., Suri and Jack, 2016), and political mobilization (e.g., Manacorda and Tesei, 2020; Gonzalez, 2021).

2002 and the licensing of GSM operators, mobile phone coverage expanded quickly—with Roshan emerging as the largest provider—and mobile access rose from 0.1% in 2002 to 37% in 2009, reaching even remote villages ([Kelly and Souter, 2014](#)). Together, these changes make Afghanistan a compelling setting to study whether mobile technology can shift gender norms.

We obtain our results by combining three main data sources. First, we use administrative records from Roshan, Afghanistan’s largest mobile operator, on the location and installation dates of all its towers between 2006 and 2013, merged with district shapefiles and population estimates to construct measures of tower density per district-year. Second, we use the Survey of the Afghan People (SAP), a nationally representative repeated cross-section conducted by the Asia Foundation, which includes detailed questions on attitudes toward female education, employment, and leadership. Our analysis covers 54,236 respondents across the 2006–2013 waves. Finally, we use long-run lightning strike intensity from NASA satellite data to instrument for mobile phone expansion.

Our empirical strategy leverages spatial and temporal variations in mobile phone towers per capita. However, tower site selection and signal strength are influenced by various geographic and topographic factors. Among these, lightning strikes play a significant role in disrupting mobile phone connectivity and slowing network expansion by causing infrastructure damage, service interruptions, and increased maintenance costs ([Andersen et al., 2012](#); [Zeddami and Day, 2014](#)). To address potential endogeneity in site selection and mobile phone access, we use district-level lightning density as an instrumental variable for tower expansion. The use of lightning density as an instrumental variable is well-established in the literature, including studies such as [Mensah \(2024\)](#), [Yu et al. \(2023\)](#), [Manacorda and Tesei \(2020\)](#), [Guriev et al. \(2020\)](#), and [Andersen et al. \(2012\)](#). Data on lightning strikes is sourced from NASA.

Using our IV approach, we find that increased mobile access significantly improved attitudes toward women’s education and employment in Afghanistan between 2006 and 2013, a period of rapid mobile connectivity expansion. The results are driven pri-

marily by shifts in men's views, as women already held more progressive attitudes. We find no overall change in perceptions toward women in leadership roles, though women themselves exhibit increased support for female leadership. To assess the validity of the exclusion restriction, we first show that lightning strikes predict outcomes in the reduced form, but the relationship disappears once we control for tower coverage. Second, in a restricted sample of districts with no towers, the instrument shows no correlation with the outcomes.

We examine potential mechanisms linking mobile phone expansion to changes in gender attitudes, focusing on two broad channels: (i) an *information channel* where phones expand access to diverse views, reduce preference falsification, and facilitate belief updating, and (ii) a *labor supply channel* where increased female employment visibility and bargaining power may shift norms. While data limitations prevent direct testing of the information channel, we find evidence that mobile access raises women's contributions to household income at the intensive margin. However, IV mediation analysis indicates labor market participation explains a small share of the documented effect on attitudes. The results therefore point to direct channels, likely through expanded information and network exposure, as the primary drivers.

Lastly, we examine whether the attitudinal changes associated with mobile phone expansion translated into tangible improvements in women's educational attainment, labor market participation, and political representation. Using lagged measures of phone access to capture delayed effects, we find evidence of positive impacts on female schooling, particularly on the likelihood of attending high school and university. The estimated effects on female labor force participation and election outcomes are also positive in magnitude, although they remain statistically imprecise, likely reflecting limited sample size and statistical power.

Our study primarily contributes to the literature on the socio-economic impacts of mobile phones. A growing body of research has examined various dimensions of mobile phones. For instance, mobile phones have been shown to enhance political mobilization during economic downturns in Africa ([Manacorda and Tesei, 2020](#)), lower

grain prices in Niger by improving market efficiency (Aker, 2010), boost sales of perishable crops such as bananas in remote Ugandan communities (Muto and Yamano, 2009), increase efficiency in India’s fishing markets (Abraham, 2006), and improve student test scores in Niger through mobile-based educational interventions (Aker et al., 2012a). While much of this literature focuses on economic and political outcomes, our study shifts the focus to the effects of mobile phones on social norms.

Another strand of literature has broadly examined the effects of information technology. Callen and Long (2015) and Gonzalez (2021) found that mobile phone interventions reduced election fraud. Andersen et al. (2012) found that internet access reduced corruption, while Guriev et al. (2020) demonstrated that uncensored 3G internet exposure lowered government approval by revealing corruption. Yu et al. (2023) showed that broadband internet alleviated labor market frictions, improving firm-level labor allocation. Additionally, internet access decreased voter turnout by altering media consumption patterns (Falck et al., 2014). However, to the best of our knowledge, no study has specifically investigated the role of technology in shaping social norms, particularly gender roles.

The remainder of the paper is structured as follows: Section 2 provides the research context, while Section 3 outlines our empirical strategy. Section 4 details the data sources, and Section 5 presents the empirical findings. Finally, Section 8 offers concluding remarks.

2 Context

In the first two decades of the 21st century, the telecommunication industry made remarkable progress in Afghanistan. In 2002, only 0.1% of the country’s population had access to private mobile phones. This number increased to 37% in 2009 and 58% in 2020. The telecommunication infrastructure expanded to remote rural areas (Kelly and Souter, 2014). In 2014, 81.1% of adults reported access to mobile phone and 62.2% said they personally had a mobile phone. However, in the same year, only 12.3%

of adults had access to internet ([U.S. Agency for Global Media, 2015](#)). In 2021, the average phone holding was 0.55 phones per person ([World Data, 2025](#)). The price of a SIM card fell from US\$300 in 2002 to US\$1 in 2009. In the same year, consumers spent an average of US\$12 per month on mobile phone services ([Wharton Knowledge, 2009](#)).

There were four major players in Afghanistan's telecommunication industry. The Afghan Wireless Communication Company (AWCC) was the first to introduce a phone network in the 1990s. However, its operations were disrupted by the civil wars and the Taliban's takeover in 1996. The company resumed services in 2002. In 2003, the second Global System for Mobile Communications (GSM) license was awarded to the Telecom Development Company Afghanistan Ltd., known as Roshan. The Lebanese company Investcom, later acquired by South Africa's MTN Group, entered the market in 2005. Etisalat, based in the United Arab Emirates, received the fourth GSM license in 2007 ([Wharton Knowledge, 2009](#)). In the later years, Afghan Telecom and Wasel Telecom also entered the market.

Our analysis is based on Roshan towers. As the first private provider of telecommunication services, Roshan emerged as the leading GSM network. Within just three years of operation, by 2006, it had captured over 50% of the market and expanded into remote areas where no other provider had reached. Holding 32% of the market share in 2012, Roshan was still largest provider ([Hamdard, 2012](#)). Roshan also pioneered several services, including short message service (SMS), General Radio Packet System (GRPS), public call offices (PCOs), and Afghanistan's first M-PESA service, enabling mobile phone-based money transfers via SMS ([Wentz et al., 2008](#)). As a result, Roshan provides a strong representation of GSM network coverage across Afghanistan.

With the fiber optic backbone limited to the country's ring road, Afghanistan's telecommunication infrastructure primarily depended on cellular towers. As of 2012, the country had 4,428 telecom base stations (BTS) ([Hamdard, 2012](#)), with Roshan accounting for nearly 32% of these facilities. Figure 1 illustrates Roshan's coverage, which extended across all Afghan provinces. The proportion of districts with at least one Roshan tower grew significantly, from zero in 2003 to more than 60% by 2013.

Similarly, by 2009 all provinces in Afghanistan had at least one Roshan tower. Most tower stations were concentrated along the country's ring road, with the highest density found in the southeastern and northern regions.

The information and communication technology (ICT), as it bridges local governments, communities and individuals with population hubs and centers of information, influenced the Afghan society in many ways. By connecting individuals to broader networks, mobile phones facilitated awareness campaigns and employment opportunities, particularly for women who might otherwise face mobility restrictions (Heinrich Böll Foundation, 2018). It also provided a platform for promoting gender equality. The interplay between mobile phone access and cultural norms is thus a critical area of inquiry, particularly concerning its impact on attitudes toward female education, labor force participation, and leadership.

3 Empirical Strategy

Estimating the causal effect of mobile phone access on gender norms presents a key empirical challenge. The expansion of mobile phone infrastructure is not random across districts. Mobile network operators may strategically deploy towers in areas with characteristics correlated with social attitudes. More broadly, districts experiencing faster modernization or economic growth may simultaneously experience greater mobile phone expansion and changing cultural attitudes, generating concerns about omitted variable bias and reverse causality.

To assess the extent of observable selection, Table A7 examines geographic, demographic, and socioeconomic predictors of mobile infrastructure expansion across districts. The results suggest that district population is the strongest and most consistent predictor of mobile technology measures, while socioeconomic and demographic characteristics display limited and inconsistent predictive power across specifications.²

²The finding that district population is the strongest predictor of mobile infrastructure expansion is consistent with the operating strategies of mobile network operators in low-income settings, where infrastructure deployment decisions are primarily driven by expected subscriber base and market size (GSMA, 2020).

While we directly account for population in the empirical analysis, concerns about unobserved determinants of tower placement and reverse causality still remain.

To address these concerns, we combine two complementary empirical strategies. First, we exploit the panel structure of the data and incorporate province-by-year fixed effects, allowing comparisons within the same province and year while accounting for province-specific time-varying shocks. Second, to address remaining concerns related to endogenous tower placement and reverse causality, we employ lightning strike density as an instrumental variable. The latter strategy leverages district-level variation in lightning strike frequency to predict mobile phone expansion rates. [Andersen et al. \(2012\)](#) show that lightning strikes hinder digital technology adoption by raising the costs of tower construction due to voltage fluctuations. Similarly, [Zeddam and Day \(2014\)](#) demonstrate that mobile broadband infrastructure is highly vulnerable to lightning-induced power surges, causing damage, faster depreciation, and increased operating costs.

Our empirical strategy can be expressed as the following system of equations:

$$Tower_{jt} = \beta_0 + \beta_1 Lightning_j + X'_{ijt}\theta + \alpha_{pt} + \varepsilon_{ijt} \quad (1)$$

$$Y_{ijt} = \omega + \gamma Tower_{jt} + X'_{ijt}\delta + \alpha_{pt} + u_{ijt} \quad (2)$$

where Y_{ijt} is the outcome for individual i in district j and year t . These outcomes capture individual-level, self-reported attitudes toward women, including views on female education, employment, and women serving in leadership positions. Section 4 describes these variables in detail. $Tower_{jt}$ is the number of mobile phone towers per 100,000 people in district j and year t .³ Section 4 provides additional details on the construction of this measure. We scale towers by population to ensure comparability across districts of different sizes. This scaling is also intuitive in our setting because the median district in Afghanistan has a population close to 100,000. As a result, a one-unit increase in this measure approximately corresponds to the addition of one tower

³As a robustness check, we also use the total number of towers while directly controlling for district population and obtain similar results.

in the median district. Moreover, districts have a median of two towers and an average of four towers during our sample period, implying that a one-unit increase represents a realistic and economically meaningful expansion in network infrastructure for the typical Afghan district.

The variable $Lightning_j$ is the maximum lightning intensity in district j from 1998 to 2013, which serves as an instrument for mobile phone tower density. X'_{ijt} is a vector of individual-level control variables (e.g., age, gender, ethnic group) that are included in both equations. α_{pt} are province-by-year fixed effects that account for province-specific, time-varying factors, and ε_{ijt} and u_{ijt} are error terms. We employ province-by-year rather than district fixed effects because lightning intensity is measured at the district level and is time-invariant. As a result, district fixed effects would absorb the instrument. We note that although $Tower_{jt}$ and $lightning_j$ vary only at the district level, the equations are estimated on the individual-level dataset with standard errors clustered at the district level. We describe our outcomes of interest and other variables in the next Section 4 in detail.

Our identification strategy relies on the exclusion restriction that district-level lightning strike intensity affects attitudes toward women only through its impact on mobile phone network expansion. That is, conditional on controls and fixed effects, lightning strikes influence cultural attitudes solely by raising the cost and slowing the rollout of mobile phone infrastructure, rather than through any direct effect on social norms. This assumption is plausible because lightning intensity is determined by geographic and topographic conditions and is orthogonal to cultural, religious, or institutional determinants of gender attitudes.

A potential concern is that lightning intensity may be correlated with other district characteristics, such as remoteness, economic development, or conflict exposure, which could independently shape social attitudes. Existing work suggests that while lightning is correlated with topography and climate, it does not directly predict political preferences, social values, or gender norms once geographic and economic factors are accounted for (see, e.g., [Andersen et al., 2012](#); [Manacorda and Tesei, 2020](#)). More-

over, studies using lightning-based instruments in related contexts show no evidence of direct effects on political or social outcomes beyond infrastructure access (Zeddham and Day, 2014; Guriev et al., 2020). Province-by-year fixed effects, included in all specifications, absorb time-varying regional shocks and compositional differences that may affect attitudes. In Section 5.2 we formally examine potential violations of the exclusion restriction.

4 Data and Measurement

We use two primary sources of data. For mobile phone access data we use information on the locations (latitude and longitude) and installation dates of cell towers operated by Roshan, Afghanistan’s largest mobile network operator during the study period. The data were provided directly by Roshan.⁴ For reference, panel A of Figure 1 presents the spatial distribution of towers on a map of Afghanistan for our entire sample period, while panel B displays a time series of the share of Afghan districts and provinces with at least one Roshan tower. These figures highlight substantial geographic and temporal variation in cell phone access. Note that by 2013 more than 60 percent of districts had access to coverage. This share grew from 30 to 60 during our sample period (2006-2013). We leverage this rich spatial and temporal variation in coverage to construct our primary measure of mobile phone availability. Specifically, we combine the tower location and timing data with district shapefiles to create panel that records the number of towers per district-year within our sample period. Additionally, we create a population-adjusted measure that scales the number of towers per 100,000 residents in a given district-year. We obtain estimates of district-year population from the Gridded Population of the World (GPW) collection (NASA, 2020). The dataset provides population estimates for a grid with a 30 arcseconds resolution (about 1kmX1km at the equator).⁵

⁴We thank Tarek Ghani and the Afghan Telecommunications Regulatory Agency (ATRA) for providing access to tower location data

⁵The GPW is available every five years between 2000 and 2020. We interpolate district population in the non-survey years by dividing the 5-year population growth rate in each district by five and using

Another data set is the Survey of the Afghan People (SAP). SAP, carried out by the Asia Foundation from 2006 to 2019, serves as an essential resource for understanding cultural attitudes in Afghanistan. This survey is provincially representative, with each round offering an independent cross-sectional view. For our study, we obtained secure access to the SAP dataset. For comprehensive details on the survey methodology and data collection, please refer to [Akseer et al. \(2019\)](#). Our analysis is centered on the 2006-2013 rounds of the SAP dataset, corresponding to the availability of our mobile phone tower data. These rounds feature an extensive set of questions that specifically address gender attitudes, including views on education, employment, and leadership. Despite the richness of the SAP dataset in providing insights into perceptions and attitudes of the people of Afghanistan, it has certain limitations. Primarily, it is not a panel survey, so individual tracking over time is not feasible. We have combined cross-sections from various survey rounds and included survey round dummies to account for year-specific variations.

Table 1 presents a summary of SAP dataset. The survey is consist of 54236 individuals, of which 57% were men and 43% women. The average respondent's age was 34.78 years, of whome 78% were married. 22% of the respondents lived in the capital, Kabul.

We measure cultural attitudes toward women using three variables: support for female education, female employment, and women in leadership roles. These are assessed at the individual response level, where a response indicating support is coded as 1, and 0 otherwise.

For the IV, we collected lightning intensity data from NASA's Global Hydrology Resource Center, DAAC ([Albrecht et al., 2016](#)). This data is derived from satellite images, which provides a $0.1^\circ \times 0.1^\circ$ resolution of lightning intensity, averaged from 1998 to 2013. We combined this data with Afghanistan district map and extracted the highest lightning intensity for each district based on the average from 1998 to 2013 to use as the IV.

this growth rate year over year within the 5-year interval.

5 Results

5.1 Main Results

We begin by exploring whether the expansion of mobile phone towers is a reliable proxy for mobile phone access. To do so, we examine the relationship between towers per 100,000 people and phone ownership using survey data. The SAP includes a question on phone ownership, allowing us to construct a binary variable equal to 1 if the respondent reported personally owning a mobile phone or having one in their household, and 0 otherwise. We then estimate an OLS specification in which this individual-level phone ownership variable is regressed on mobile tower availability. Table 2 presents the results. Column (1) reports the baseline correlation without additional controls or fixed effects. Columns (2) and (3) progressively incorporate individual-level controls and fixed effects. Across all specifications, the coefficient on towers per 100,000 people remains positive and statistically significant. Overall, the results suggest that tower expansion is strongly associated with realized phone ownership and therefore provides a reasonable proxy for mobile phone access in our setting.

Next, we discuss our main results. Table 3 presents the first stage results from estimating Equation 1. The specification includes year fixed effects, province fixed effects, province-specific time trends, and individual-level controls such as gender, age, income and ethnicity. We find a strong negative correlation between district towers per 100,000 and lightning intensity. This suggests that lightning and the disruptions it causes played a significant role in shaping mobile phone service expansion.

Table 4 presents our main results from estimating Equation 2. For each outcome, we report OLS and instrumental variable (2SLS) estimates. The OLS specifications estimate the relationship between mobile phone tower density and attitudes toward women, while the 2SLS specifications instrument tower density using district-level lightning intensity to address potential endogeneity in the placement of mobile phone infrastructure.

The results show that mobile phone expansion is associated with more favorable

attitudes toward women's education and employment. In the IV specifications, a one-unit increase in towers per 100,000 people increases support for female education by 1.8 percentage points and support for female employment by 2.9 percentage points. Given that the median Afghan district at the beginning of the sample period had a population close to 100,000, we can interpret these estimates as the deployment of one additional tower in a typical district increased support for female education and employment by approximately 2 and 3 percentage points, respectively.

These effects are meaningful given the nature of the intervention and the outcomes examined. Mobile phone expansion represents a broad communication technology rather than a targeted program designed to shift gender attitudes. The fact that access to this general-purpose technology generated measurable changes in views toward women's education and employment suggests that communication infrastructure can influence social norms even in settings where such norms are deeply rooted. The effects are also concentrated in norms closely related to information access and economic opportunities: we find no evidence that mobile phone expansion affected attitudes toward women serving in leadership positions.

We also note that the IV estimates are much larger than the corresponding OLS estimates, which is consistent with attenuation from measurement error in tower density and/or non-random placement of mobile phone infrastructure. Overall, the results indicate that mobile phone expansion contributed to incremental but meaningful shifts in attitudes toward women's roles in society.

Table 5 examines whether the effects of mobile phone expansion differ by gender. We estimate the IV specification separately for male and female respondents. The results suggest that the overall effects are driven primarily by changes in men's attitudes toward women's education and employment. Among male respondents, a one-unit increase in towers per 100,000 people increases support for female education by 2.4 percentage points and support for female employment by 3.6 percentage points. These effects are statistically significant and larger than the corresponding estimates in the full sample.

In contrast, we find no statistically significant changes in women's attitudes toward female education or employment. This pattern is consistent with women having substantially more favorable baseline attitudes in the sample. While 92 percent of female respondents already supported female education and 80 percent supported female employment, support among male respondents was considerably lower (81 percent and 53 percent, respectively). Thus, mobile phone expansion appears to have had larger effects among the group with greater scope for changes in attitudes.

For attitudes toward women in leadership positions, the pattern differs. Although the aggregate estimates show no significant effect, mobile phone expansion increases support for female leadership among women by 3.1 percentage points. Given that baseline support for female leadership among women was only 14.5 percent, this represents a meaningful relative increase in support for an outcome where initial attitudes were substantially less favorable. These heterogeneous effects suggest that mobile phone access may influence different dimensions of gender attitudes through distinct channels, with larger effects on views related to education and employment among men and potential changes in perceptions of women's leadership roles among women.

We also examine heterogeneity by ethnicity. Afghanistan is ethnically diverse, with multiple ethno-linguistic groups, although the absence of a recent national census means that the population shares of these groups are uncertain. In the SAP, 43 percent of respondents identify as Pashtoon. Pashtoos are geographically widespread but are primarily concentrated in the southern and eastern regions of the country, areas where the Taliban first emerged in the mid-1990s (Nojumi, 2002). Given this historical context, and the possibility that prolonged exposure to conflict and Taliban governance may have contributed to differences in gender norms across communities, we examine whether the effects of mobile phone expansion differ between Pashtoon and non-Pashtoon respondents.

Table 6 presents these results. We find that mobile phone expansion increases support for female education among both Pashtoon and non-Pashtoon respondents. The estimated effects are 1.5 percentage points for Pashtoos and 2.4 percentage points for

non-Pashtoons, suggesting that access to communication technology affected views on female education across ethnic groups.

The results differ for attitudes toward female employment. Among non-Pashtoon respondents, a one-unit increase in towers per 100,000 people increases support for female employment by 5.7 percentage points, a relatively large effect given a baseline level of support of 72.7 percent. In contrast, we find no statistically significant effect among Pashtoon respondents. This pattern suggests that while mobile phone access influenced views on female education broadly, changes in attitudes toward women's participation in the labor force were more concentrated among non-Pashtoon communities.

5.2 Tests of Exclusion Restriction

We assess the exclusion restriction in three ways. First, in Table 8, we present two sets of regressions. Columns (1), (3), and (5) report reduced form estimates, where the outcomes are regressed directly on the instrument. In theory, the instrument should be significantly related to the outcomes, but its effect should operate solely through the endogenous variable. Consistent with this expectation, we find significant estimates in these columns. To test whether the endogenous variable, phone towers, is indeed the only channel through which the instrument affects the outcomes, we include it as a control in columns (2), (4), and (6). If the exclusion restriction holds, the coefficients on the instrument should become statistically insignificant when conditioning on the endogenous variable. This is precisely what we observe, supporting the validity of the exclusion restriction.

Second, we estimate a reduced form regression using a restricted sample that includes only districts without any towers. The goal of this exercise is to demonstrate that, in the absence of the endogenous variable, the instrument should not be correlated with the outcomes. As shown in Table 9, the coefficients on the instrument are statistically insignificant, which supports the validity of the exclusion restriction.

Third, Table 7 examines the robustness of the IV estimates to the inclusion of a

rich set of baseline district characteristics. In columns (1), (3), and (5), we augment the vector of controls, X_{ijt} , to include district-level measures of geography, demographics, education, ethnicity, and economic conditions. Specifically, we control for elevation, log population, educational attainment, ethnic composition, income, mean age, and the female population share, all measured at the beginning of the sample period. In columns (2), (4), and (6), we further interact each baseline characteristic with survey-year indicators, allowing districts with different initial characteristics to follow distinct trajectories over time.⁶

The results are highly consistent with the baseline estimates. The positive and statistically significant effects of mobile phone access on attitudes toward female education and employment remain largely unchanged in magnitude and significance across all specifications.

These findings address the concern that lightning intensity may be correlated with underlying district characteristics that independently shape the evolution of gender norms. Even after allowing districts with different initial demographic, educational, economic, and ethnic characteristics to exhibit flexible year-specific trends, the estimated effects remain stable. The first-stage relationship weakens modestly relative to the baseline specification but remains comfortably above conventional thresholds.

5.3 Robustness Checks

In this section, we examine the internal validity of our results. First, we replace mobile phones per 100,000 population with the number of cellular towers while controlling for population. This approach allows to test whether the estimated effect of mobile phone access on gender norms is sensitive to how access is measured. By including population as a control, the specification isolates variation in tower availability that is not simply driven by the size of the underlying market. Results in Table A1 is in the

⁶Formally, the control vector (X_{ijt}) includes both characteristics that vary at the individual-survey-year level and baseline district characteristics interacted with survey-year indicators. The latter terms take the form $X_j \times \mathcal{I}(t)$, where X_j denotes a district-level characteristic measured at baseline and $\mathcal{I}(t)$ denotes a set of survey-year indicators, allowing the relationship between baseline district conditions and outcomes to vary flexibly over time.

same direction as our main estimates in Table 4. The size of the coefficient is larger because of the difference in scale.

Second, Afghanistan has 34 provinces, and our analysis is conducted at the district level. Districts within the same province may share unobserved characteristics related to culture, economic conditions, or administrative practices. To address this concern, Table A2 reports results with standard errors clustered at the province level. This estimation accounts for possible correlation of errors within provinces. The estimates and their standard errors remain very similar to the baseline results, which suggests that the findings are not driven by province level clustering or other unobserved factors shared across districts within a province.

Third, geographically large districts may require a greater number of towers simply to achieve adequate coverage, even if the level of mobile phone access is similar across districts. To account for this possibility, Table A3 presents results using towers per square kilometer as the independent variable. This measure adjusts tower availability for the size of the district and therefore helps distinguish between infrastructure that is needed for basic geographic coverage and infrastructure that reflects meaningful variation in network access. The point estimates are larger than those in the main specification, which arises from the difference in scale rather than a substantive change in the underlying relationship. The consistency of the results across these two ways of measuring tower presence supports the idea that the estimated effects are not driven by differences in district size or by the need for more towers in larger areas.

Fourth, we assess the sensitivity of our findings to a different functional form. Because the outcome variables in our study are binary, our main specification uses a linear probability model for ease of interpretation and transparency in the IV setting. To check whether the results depend on this choice, Table A4 reports estimates from an IV probit model, which imposes a nonlinear structure more consistent with a binary response framework. The IV probit results closely match those from the linear probability model, indicating that our conclusions are not driven by the choice of functional form and that the estimated relationship is stable across alternative specifications.

Moreover, in Table A5, we replace our main instrument—maximum lightning intensity between 1998 and 2013—with the mean lightning intensity over the same period. Lightning intensity exhibits limited year-to-year variation within districts, which makes the mean a relatively flat measure that captures little meaningful cross-district difference. Using the maximum instead allows us to exploit the highest recorded levels during the period, which creates more dispersion in the instrument and therefore provides a stronger source of exogenous variation for predicting tower deployment. When we use the mean measure, this variation is substantially compressed, and the instrument becomes weaker. Consistent with this expectation, the IV estimates based on the mean lightning variable are smaller and less precise, indicating that the maximum measure is better suited for capturing the limited spatial variation in lightning exposure that influences the siting of mobile infrastructure and, consequently, gender norms.

We also examine the sensitivity of our results to potential spillover effects. Because our unit of analysis is the district, residents in districts with few or no towers may still benefit from coverage if they are located near districts with greater tower density. Such spillovers would tend to attenuate the estimated effect of tower deployment, biasing our coefficients toward zero. To address this concern, we exclude districts without any towers that border districts with at least one tower, thereby removing areas where spillover exposure is most likely. The results, presented in Table A6, remain consistent with our main estimates and are in fact larger in magnitude, which aligns with the prediction that spillover effects would bias the baseline results downward.

Finally, a remaining concern is that lightning intensity is fixed across districts. In our baseline specification, the first stage assumes that the relationship between lightning intensity and tower deployment is constant over time. To relax this assumption, we estimate Equation (1) using district-level lightning intensity interacted with survey-year indicators as instruments.

Table A8 reports the results from this specification. The estimated effects of mobile phone access on attitudes toward women remain very similar to the baseline esti-

mates. These results suggest that our findings are not driven by imposing a constant first-stage relationship throughout the mobile network rollout period. We note that the interacted instrument reduces our first stage because the identifying variation is distributed across multiple year-specific instruments. We therefore view this exercise as a robustness check that relaxes the identifying variation assumption of the baseline instrument rather than our preferred specification.

6 Mechanisms

This section discusses potential mechanisms through which mobile phone access can influence attitudes toward women’s education, employment, and leadership. We focus on two broad channels: an information channel and a labor supply channel. The information channel highlights how mobile phones expand the set of information individuals are exposed to and reshape the structure of their social networks. The labor supply channel emphasizes how phones affect women’s labor market participation directly, which can, in turn, shift cultural norms through increased visibility and household bargaining power. Figure 3 presents a graphical representation of these mechanisms.

6.1 Information Channel

Mobile phones can influence cultural attitudes by expanding the set of information available to individuals and by fundamentally reshaping the structure of their social networks. These changes affect both the type of information to which individuals are exposed and the context in which beliefs are formed, expressed, and updated.

6.1.1 Network Structure

First, mobile phones fundamentally change the structure of an individual’s social network. Mobile phones make an individual’s network more geographically extensive. This is represented in the change from panel (a) to panel (b) in Figure 2. They can also

increase interactions with more distant nodes of the network, such as those in provincial centers or the capital. This is represented in the change from panel (a) or (b) to panel (c) in Figure 2. As these interactions become more frequent, individuals can be exposed to alternative narratives and behaviors, including more progressive views on gender roles. This can lead to belief updating as individuals integrate new information into their existing priors (e.g., learning that women in Kabul work outside the home, or that educating girls pays off) (Bursztyn et al., 2020; Centola, 2010). Belief updating may also occur through exposure to role models (e.g., learning about a female cousin working in a school or NGO) (Porter and Serra, 2020; Serra, 2022; Kipchumba et al., 2024). We refer to this as the network exposure subchannel in Figure 3.

Second, phones can reshape how individuals interact within their network by increasing the privacy of communication. This can reduce the social cost of expressing support for views that deviate from traditional gender norms. More importantly, private interactions can reveal that others share similar views, even if those views are not publicly expressed (Bursztyn et al., 2020). This, in turn, can reduce preference falsification (e.g., a father who supports his daughter's schooling may be more willing to publicly discuss it and send her to school if he knows others privately hold similar views). We refer to this as the latent preferences subchannel in Figure 3. Mobile phones lower the cost of expressing and acting on privately held beliefs, allowing latent attitudes to surface and potentially spread (Kuran, 1995).

6.1.2 General information

Mobile phones expand the general information set available to individuals (Aker, 2010; Jensen, 2007). This includes access to information from outside the network such as news, educational campaigns, NGO messaging, and other forms of information that present alternatives to traditional gender roles. This mechanism complements the previous subchannels by providing top-down exposure to additional information that reinforces belief updating and latent preferences to surface. We refer to this as the general information subchannel in Figure 3.

Together, these two subchannels—network structure and general information access—comprise the broader information channel through which mobile phones may influence attitudes toward women’s roles in education, employment, and leadership.

6.2 Labor Supply Channel

Mobile phones can also influence cultural attitudes through their direct effects on women’s labor market participation. Phones reduce job search friction, increase economic activity, and improve access to employment opportunities (Dammert et al., 2015; Klonner and Nolen, 2010; Nsabimana and Funjika, 2019; Aker and Mbiti, 2010). These direct impacts on labor supply can, in turn, reshape gender norms through two complementary mechanisms.

First, as women participate in the labor force, their visibility in these roles can normalize such behavior and prompt shifts in norms among others in the community. For example, seeing women employed in education, health, or NGO work may lead to belief updating about gender roles. We refer to this as the labor market visibility subchannel in Figure 3. (Bursztyn et al., 2020)

Second, women’s labor market participation—and subsequent earnings—can increase bargaining power within the household. Economic models of intra-household decision-making suggest that individuals who contribute income or control financial assets often gain greater influence over household decisions (Duflo, 2012; Qian, 2008). In this context, even modest earnings can allow women to shape decisions related to their own mobility, education, or engagement with public life. We refer to this as the household bargaining subchannel in Figure 3.

Taken together, the labor supply channel operates through a two-step process: mobile phones expand access to work opportunities for women, and this economic participation then facilitates norm change through visibility effects and increased household bargaining power.

6.3 Other Channels

Finally, it is also possible that mobile phones affect gender norms through channels beyond information and labor supply. One such channel is improved coordination of collective action. Mobile phones can facilitate coordination among more progressive actors such as NGO workers, teachers, or parents who support changes to gender norms. This can lead to coordinated actions to accelerate norm change (Kuran, 1995; Centola, 2010).

Another potential channel involves mobile finance and remittance flows. Mobile phones may facilitate income transfers to women through platforms such as M-Paisa, potentially increasing their access to financial resources (Suri and Jack, 2016). This, in turn, may strengthen women's bargaining power in household decision-making. We consider this mechanism as complementary to the household bargaining subchannel discussed above.

Phones may also directly expand access to educational content, particularly in areas where girls face barriers to in-person schooling (Aker et al., 2012b; Aker and Ksoll, 2019). To the extent that girls engage with these resources, this may increase the visibility and perceived feasibility of female education and prompt belief updating in a way similar to the labor market visibility subchannel.

The mechanisms discussed above highlight several ways through which mobile phone access may influence gender attitudes. In the empirical analysis that follows, we focus on the two primary channels: the information channel and the labor supply channel. Specifically, we examine whether mobile phone expansion affects women's economic participation and earnings, which provides evidence on the labor supply pathway. We interpret the remaining effect on gender attitudes as potentially reflecting changes coming from the information pathway. Other channels, such as collective action, mobile finance, or access to educational content, may also contribute to changes in gender attitudes but are not directly tested in this analysis.

6.4 Evidence on the Mechanisms

We focus our empirical analysis on the two primary mechanisms discussed above: the information and labor supply channels. The information channel is not directly observable in our data and therefore cannot be tested directly. In contrast, the labor supply channel yields testable implications.

We proceed in two steps. First, we examine whether mobile phone expansion affects women's labor supply and economic contributions within the household. The purpose of this exercise is to assess whether there is indeed a labor supply response.

Second, we assess whether there is a response in attitudes that is driven by observed changes in labor supply. Specifically, we study the relative importance of the labor supply and information channels using a mediation framework in which measures of labor supply serve as mediators. Under this approach, we can estimate the portion of the total effect accounted for by mobile phone-driven changes in labor supply (indirect effect), while the remaining (direct) component reflects other mechanisms. From a theoretical standpoint, the information channel is a primary candidate for this direct effect. Information is not a downstream feature of the technology and does not operate through some mediator but is rather a core aspect of what phone access provides before anything else. Although this strategy does not allow us to cleanly identify the information mechanism (or its subchannels: network structure and general information), it helps gauge its potential importance relative to the labor supply channel.

In Table 10, we assess the impact of mobile phone expansion on indicators of female employment. Specifically, we use two variables reported in SAP: whether women within the household contribute to household income, and whether their contribution exceeds 25% of total household income. The former serves as a proxy for employment at the extensive margin, while the latter captures effects at the intensive margin. Although we do not find statistically significant effects on the likelihood of contributing to household income, we observe a meaningful increase in women's contributions, suggesting that mobile phone access may enhance female labor earnings for those already working. This suggests that any effect on norms operating through the labor

supply mechanism are likely the result of changes in household bargaining due to an increased share of financial contribution to the household by women.

Next, we employ the mediation analysis framework of [Dippel et al. \(2019\)](#) to gauge the relative importance of the labor supply and information channels.⁷ This causal mediation framework estimates the effect of treatment T (mobile phone expansion) on outcome Y (attitudes) through a mediator M (labor supply), using the same instrument Z (lightning strike intensity). It decomposes the total effect γ , estimated in Equation (2), into an indirect effect via M and a direct effect. As shown in Figure 4, γ_D captures the direct effect of mobile phone expansion (T) on attitudes toward women (Y). Given the nature of the technology, we interpret this direct effect as reflecting the information channel, as access to a mobile phone inherently expands individuals' exposure to information and reshapes their communication networks. γ_M^T reflects the impact of mobile phone expansion (T) on female labor force participation (M), and γ_Y^M represents the effect of female labor force participation (M) on attitudes toward women (Y).

To implement the IV mediation framework described in Figure 4, we define mediator M_{ijt} using the two definitions described above: (i) an indicator equal to one if women report contributing more than 25% of total household income (intensive margin) and (ii) an indicator for contributing any positive amount (extensive margin).

The mediation procedure consists of two 2SLS systems. First, we estimate the effect of mobile phone expansion on the mediator:

$$Tower_{jt} = \beta_0 + \beta_1 Lightning_j + X'_{ijt}\theta + \alpha_{pt} + \varepsilon_{ijt} \quad (3)$$

$$M_{ijt} = \alpha_0 + \gamma_M^T Tower_{jt} + X'_{ijt}\beta + \alpha_{pt} + v_{ijt} \quad (4)$$

where Equation (3) is simply the first stage from the main IV estimation (i.e., Equation(1)) and the remaining variables are defined as in equations (1) and (2). γ_M^T gives the effect of phone expansion on female income (i.e., $Tower_{jt}$ on M_{ijt}). Second, we estimate the effect of the mediator M_{ijt} on Y_{ijt} by instrumenting for the mediator using

⁷We estimate the method using the corresponding STATA package proposed in ([Dippel et al., 2020](#))

Lightning_j and controlling for *Tower_{jt}*:

$$M_{ijt} = \rho_0 + \rho_1 \text{Lightning}_j + \rho_2 \text{Tower}_{jt} + X'_{ijt} \psi + \alpha_{pt} + \xi_{ijt} \quad (5)$$

$$Y_{ijt} = \kappa_0 + \gamma_Y^M M_{ijt} + \gamma^D \text{Tower}_{jt} + X'_{ijt} \kappa + \alpha_{pt} + \eta_{ijt} \quad (6)$$

The coefficient γ_Y^M captures the effect of the mediator on the outcome. The total effect of mobile phone expansion on Y_{ijt} given by γ in Equation (2) can thus be decomposed into:

$$\gamma = \gamma^D + \gamma_M^T \gamma_Y^M \quad (7)$$

where γ^D denotes the direct effect and $\gamma_M^T \gamma_Y^M$ denotes the indirect (mediated) effect operating through income generation enabled by phone access.

Table 11 presents the results of the mediation analysis. We use whether women contribute more than 25% of household income as the mediator since it is the labor supply measure where we document a meaningful response to mobile phone expansion in Table 10.⁸ Total effect refers to the effect of mobile phone expansion on favorable attitudes in each of the categories we focus on (attitudes on education (column 1), employment (column 2), and leadership (column 3)). These are, essentially, the coefficients already presented in Table 3. Direct effect refers to the portion of the total effect explained by the direct channel (information). Indirect effect refers to the portion of the total effect explained by the mediator (labor supply channel).

Women's contribution to household income accounts for approximately 57% of the estimated shift in norms on female education (column 1). For norms related to female employment, women's contribution to household income explain roughly 62% (column 2). Results for norms on leadership (column 3) are very imprecise to draw any conclusion.

Overall, while the share of the total effect explained by the mediator (labor supply channel) is economically meaningful, these estimates cannot be distinguished from zero at conventional levels. In contrast, the direct effect is highly precise and statisti-

⁸Table A9 presents results using whether women in the household work as mediator and the results are qualitatively similar regardless of which definition of labor supply is used as mediator.

cally significant at the 1% level, albeit having a lower weight in explaining the total effect. A natural interpretation is the information channel: access to a mobile phone inherently expands individuals' access to information and reshapes their information network.

Taken together, the results suggest that although mobile phone expansion increases women's economic contributions within the household, this channel does not appear to be the primary driver of the observed shifts in gender norms. Instead, more direct mechanisms—most notably expanded access to information—likely play a central role.

7 Downstream Effects on Female Education, Employment, and Leadership

We next examine whether the observed shifts in gender norms translate into changes in downstream outcomes, including female education, employment, and political participation. While the previous section focuses on attitudinal change, these outcomes capture realized behavioral responses. We estimate these effects using Equations 1 and 2. To allow time for norm shifts to translate into behavior, we use a one-period lag of towers per 100,000 people rather than its contemporaneous value.⁹ Lastly, since we are focusing on downstream effects for women, we restrict our analysis to female respondents aged 18-25.¹⁰ This age group is also more likely to exhibit any response in terms of education and employment.

For education, we rely on survey questions reporting respondents' level of schooling. We construct binary indicators for key education categories, including no schooling, some high school, and some university education. We focus on high school and university given age restrictions in the sample, i.e., only women 18 or older are interviewed in SAP. We also examine an outcome about whether the respondent is cur-

⁹Results are qualitatively similar when using two period lags.

¹⁰We only impose the restriction of 25. The lower limit, 18, is the minimum age for respondents to appear in the survey.

rently a student. Table 12 reports the results for these outcomes. Across all specifications, we find no statistically significant effects on any of the education measures.

We next examine female employment outcomes using survey questions that capture women's participation in economic activities at different levels of intensity. One indicator measures whether women work at all, while another captures involvement in clerical employment. We also construct a variable measuring women's contribution to household income. Specifically, whether women contribute more than 25% of a household's monthly income. Table 13 presents the results for these employment measures, and again we find no statistically significant effects.

To assess changes in leadership, we examine the impact of mobile phone expansion on electoral outcomes for female candidates using district-level data from Afghanistan's 2010 and 2018 parliamentary elections. The data come from national vote tallies collected by the Independent Election Commission (IEC) for both elections and include candidate names, gender, district of candidacy, and vote totals. We aggregate these data to the district level to construct measures of the share of female candidates, the share of votes received by female candidates, and the share of elected candidates who are female.

Table 14 presents the results. The estimated effects of mobile phone expansion on electoral outcomes for female candidates are positive across all three measures but are not statistically significant. The magnitudes—0.025 for the share of candidates, 0.099 for vote share, and 0.031 percentage points for elected share—suggest modest improvements that are consistent with increased support for female leadership. However, these estimates are imprecise. One likely explanation is the limited sample size. Because the analysis is conducted at the district level, aggregation substantially reduces the number of observations. This limited variation likely contributes to large standard errors and the lack of statistical significance. Overall, while the direction of the estimates is suggestive of a positive response in leadership outcomes, the evidence remains inconclusive.

Taken together, the results on downstream outcomes suggest limited evidence that

the observed shifts in gender norms translate into measurable changes in behavior. This is consistent with a broader view in which changes in attitudes can precede behavioral change, but do not immediately translate into realized outcomes. Behavioral responses such as educational attainment, labor market participation, or political representation often face additional constraints. Some of these include institutional barriers, adjustment costs, and coordination frictions which may slow or attenuate the effect of shifting norms. As a result, while mobile phone expansion appears to positively affect attitudes toward women, translating this shifts into observable behavioral change may require longer time horizons or complementary changes in other constraints.

8 Conclusion

This paper examined the causal impact of mobile phone connectivity on cultural attitudes in Afghanistan, leveraging the expansion of mobile networks. Our findings indicate that greater mobile connectivity increased support for female education and women's participation in the workforce. The impact, however, varies across gender. Men became more supportive of female education and employment opportunities, while women's attitudes remained largely unchanged in these domains but showed a significant increase in support for female political leadership.

The mechanism analysis suggests that the effects of mobile phone expansion on gender norms operate primarily through increased access to information rather than through changes in women's labor supply alone. While mobile phone access appears to increase women's economic contributions within the household, the mediation results indicate that the labor supply channel explains only a limited share of the overall effect. Instead, the larger and more robust direct effect points toward the importance of the information channel, whereby phones expand exposure to new ideas, reshape communication networks, reduce the social costs of expressing latent beliefs, and facilitate belief updating regarding women's roles in society. Taken together, the find-

ings suggest that mobile phones may influence cultural change not only as economic technologies, but also as powerful tools for information diffusion and social transformation.

This study contributes to a broader understanding of how modern communication technology shapes cultural norms in developing countries. By providing access to information, alternative viewpoints, and social networks, mobile phones can drive progressive shifts in deeply ingrained societal attitudes. However, due to data limitations, we were unable to fully explore the mechanisms driving these changes and leave it for future research.

In sum, mobile connectivity serves as a catalyst for cultural and economic change by expanding access to information, increasing exposure to new ideas, and facilitating greater participation in public life. While barriers to gender equality remain, the continued growth of mobile networks offers a promising avenue for fostering social progress in Afghanistan and other developing nations.

References

- Abraham, Reuben**, "Mobile phones and economic development: Evidence from the fishing industry in India," in "2006 International Conference on Information and Communication Technologies and Development" IEEE 2006, pp. 48–56.
- Afghanistan Information Management Services (AIMS)**, "Roads of Afghanistan," 1997–2005. Vector GIS data.
- Aker, Jenny C**, "Information from markets near and far: Mobile phones and agricultural markets in Niger," *American Economic Journal: Applied Economics*, 2010, 2 (3), 46–59.
- **and Christopher Ksoll**, "Call me educated: Evidence from a mobile phone experiment in Niger," *Economics of Education Review*, 2019, 72, 239–257.
- **and Isaac M Mbiti**, "Mobile phones and economic development in Africa," *Journal of economic Perspectives*, 2010, 24 (3), 207–232.
- **, Christopher Ksoll, and Travis J Lybbert**, "Can mobile phones improve learning? Evidence from a field experiment in Niger," *American Economic Journal: Applied Economics*, 2012, 4 (4), 94–120.
- **, – , and –**, "Can mobile phones improve learning? Evidence from a field experiment in Niger," *American Economic Journal: Applied Economics*, 2012, 4 (4), 94–120.
- Akseer, Tabasum, Khadija Hayat, Emily Catherine Keats, Sayed Rohullah Kazimi, Charlotte Maxwell-Jones, Mohammed Sharih Shiwan, David Swift, Mustafa Yadgari, and Fahim Ahmad Yousufzai**, "A survey of the Afghan people: Afghanistan in 2019," 2019.
- Albrecht, Rachel I, Steven J Goodman, Dennis E Buechler, Richard J Blakeslee, and Hugh J Christian**, "Where are the lightning hotspots on Earth?," *Bulletin of the American Meteorological Society*, 2016, 97 (11), 2051–2068.
- Andersen, Thomas Barnebeck, Jeanet Bentzen, Carl-Johan Dalgaard, and Pablo Selaya**, "Lightning, IT diffusion, and economic growth across US states," *Review of Economics and Statistics*, 2012, 94 (4), 903–924.
- Antonucci, Toni C, Kristine J Ajrouch, and Jasmine A Manalel**, "Social relations and technology: Continuity, context, and change," *Innovation in aging*, 2017, 1 (3), igx029.
- Bovenberg, Ary Lans**, "Norms, values, and technological change," *De Economist*, 2002, 150 (5), 521–553.
- Bursztyn, Leonardo, Alessandra L González, and David Yanagizawa-Drott**, "Misperceived social norms: Women working outside the home in Saudi Arabia," *American Economic Review*, 2020, 110 (10), 2997–3029.
- Callen, Michael and James D Long**, "Institutional corruption and election fraud: Evidence from a field experiment in Afghanistan," *American Economic Review*, 2015, 105 (1), 354–381.
- Centola, Damon**, "The spread of behavior in an online social network experiment," *Science*, 2010, 329 (5996), 1194–1197.
- Dammert, Ana C., Jose C. Galdo, and Virgilio Galdo**, "Integrating mobile phone technologies into labor-market intermediation: A multi-treatment experimental design," *IZA Journal of Labor and Development*, 2015, 4 (1), 1–27.
- Dippel, Christian, Andreas Ferrara, and Stephan Heblich**, "Causal mediation analysis in instrumental-variables regressions," *The Stata Journal*, 2020, 20 (3), 613–626.
- **, Robert Gold, Stephan Heblich, and Rodrigo Pinto**, "Mediation analysis in IV settings with a single instrument," *Unpublished manuscript*, 2019.
- Duflo, Esther**, "Women empowerment and economic development," *Journal of Economic Literature*, 2012, 50 (4), 1051–1079.

- Falck, Oliver, Robert Gold, and Stephan Hebllich**, "E-lections: Voting Behavior and the Internet," *American Economic Review*, July 2014, 104 (7), 2238–65.
- Gonzalez, Robert M**, "Cell phone access and election fraud: evidence from a spatial regression discontinuity design in Afghanistan," *American Economic Journal: Applied Economics*, 2021, 13 (2), 1–51.
- GSMA**, "Bringing Mobile Internet to Remote Communities," Technical Report, GSM Association 2020. Accessed May 28, 2026.
- Guriev, Sergei, Nikita Melnikov, and Ekaterina Zhuravskaya**, "3G Internet and Confidence in Government*," *The Quarterly Journal of Economics*, 12 2020, 136 (4), 2533–2613.
- Hamdard, Javid**, "The State of Telecommunications and Internet in Afghanistan," Technical Report April 2012. Accessed: 2025-02-19.
- Hassani, Khalilullah**, "Impact of Military Expenditure on Economic Growth of Afghanistan," *American International Journal of Economics and Finance Research*, 2020, 2 (1), 72–82.
- Heinrich Böll Foundation**, "You Are What You Share: How Social Media is Changing Afghan Society," 2018. Accessed: 2025-02-14.
- Jensen, Robert**, "The digital divide: Information (technology), market performance, and welfare in the South Indian fisheries sector," *Quarterly Journal of Economics*, 2007, 122 (3), 879–924.
- Kelly, Tim and David Souter**, *The role of information and communication technologies in post-conflict reconstruction*, World Bank Publications, 2014.
- Kipchumba, Elijah, Catherine Porter, Danila Serra, and Munshi Sulaiman**, "The impact of role models on youths' aspirations, gender attitudes and education in Somalia," Technical Report 17261, IZA Institute of Labor Economics 2024. IZA Discussion Paper.
- Klonner, Stefan and Patrick Nolen**, "Cell phones and rural labor markets: Evidence from South Africa," 2010. Working paper.
- Kuran, Timur**, *Private truths, public lies: The social consequences of preference falsification*, Harvard University Press, 1995.
- Maley, William and William Maley**, "The Fall of the Taliban," *The Afghanistan Wars*, 2002, pp. 251–283.
- Manacorda, Marco and Andrea Tesei**, "Liberation technology: Mobile phones and political mobilization in Africa," *Econometrica*, 2020, 88 (2), 533–567.
- Mensah, Justice Tei**, "Jobs! Electricity shortages and unemployment in Africa," *Journal of Development Economics*, 2024, 167, 103231.
- Muto, Megumi and Takashi Yamano**, "The impact of mobile phone coverage expansion on market participation: Panel data evidence from Uganda," *World development*, 2009, 37 (12), 1887–1896.
- Najam, Rafiuddin, Harry Anthony Patrinos, Raja Bentaouet Kattan et al.**, "The Mis-Education of Women in Afghanistan," *The World Bank Group Policy Research Working Paper*, 2024.
- NASA**, "Gridded Population of the World (GPWv4)," *EarthData*, 2020.
- National Aeronautics and Space Administration and National Geospatial-Intelligence Agency**, "Shuttle Radar Topography Mission 30 Arc Second Finished Data," 2000. Digital elevation data.
- Nixon, Hamish and Richard Ponzio**, "Building democracy in Afghanistan: The statebuilding agenda and international engagement," *International peacekeeping*, 2007, 14 (1), 26–40.
- Nojumi, Neamatollah**, "The Rise of the Taliban," in "The Rise of the Taliban in Afghanistan: Mass Mobilization, Civil War, and the Future of the Region," Springer, 2002, pp. 117–124.
- Nsabimana, Aimable and Patricia Funjika**, "Mobile phone use, productivity and labour

- market in Tanzania," WIDER Working Paper 2019/56, UNU-WIDER 2019.
- Pearse, Rebecca and Raewyn Connell**, "Gender Norms and the Economy: Insights from Social Research," *Feminist economics*, 2016, 22 (1), 30–53.
- Porter, Catherine and Danila Serra**, "Gender differences in the choice of major: The importance of female role models," *American Economic Journal: Applied Economics*, 2020, 12 (3), 226–254.
- Qian, Nancy**, "Missing women and the price of tea in China: The effect of sex-specific earnings on sex imbalance," *The Quarterly journal of economics*, 2008, 123 (3), 1251–1285.
- Serra, Danila**, "Role models in developing countries," Unpublished working paper 2022. Forthcoming in Handbook of Field Experiments, Vol. 3.
- Suri, Tavneet and William Jack**, "The long-run poverty and gender impacts of mobile money," *Science*, 2016, 354 (6317), 1288–1292.
- Tegegn, Dagn Alemayehu**, "The role of science and technology in reconstructing human social history: effect of technology change on society," *Cogent Social Sciences*, 2024, 10 (1), 2356916.
- U.S. Agency for Global Media**, "Media Use in Afghanistan," Technical Report, U.S. Agency for Global Media 2015. Accessed: 2025-02-14.
- Wentz, Larry, Frank Kramer, and Stuart Starr**, "Information and Communication Technologies for Reconstruction and Development: Afghanistan Challenges and Opportunities," Technical Report 2008.
- Wharton Knowledge**, "An Industry on the Line: Telecommunications in Afghanistan," 2009. Accessed: 2025-02-14.
- World Bank**, "Afghanistan Development Update 2022," Technical Report, World Bank 2022. Accessed: 2025-02-14.
- World Data**, "Mobile Communication and Internet in Afghanistan," 2025. Accessed: 2025-02-14.
- Yu, Li, Tiemeng Ma, Sirong Wu, and Zhuoyang Lyu**, "How does broadband internet affect firm-level labor misallocation: The role of information frictions," *China Economic Review*, 2023, 82, 102067.
- Zeddani, Ahmed and Phil Day**, "Improving the protection of ICT equipment against lightning strikes," Technical Report 2014.

Table 1: Summary Statistics

| | Share (Mean) |
|------------------------------|--------------|
| Regions: | |
| ... The Capital (Kabul) | 0.22 |
| ... East | 0.09 |
| ... Southeast | 0.10 |
| ... Southwest | 0.16 |
| ... West | 0.12 |
| ... Northeast | 0.13 |
| ... Northwest | 0.12 |
| ... Central | 0.22 |
| Demographic characteristics: | |
| Male | 0.57 |
| Married | 0.78 |
| Age | 34.78 |
| Household size | 9.52 |
| Household income | 5.27 |
| Number of observations | 54236.00 |

Notes: Numbers < 0 represent ratios. Data covers 2006-2013. The sample size for all years were between 6000 and 10,000. Sampling was conducted at the province level and data was collected across districts. Surveys were independent cross section of individuals.

Table 2: Phone Ownership and Mobile Towers

| | Phone ownership | | |
|---------------------------|---------------------|---------------------|---------------------|
| | (1) | (2) | (3) |
| Towers per 100,000 people | 0.048*** (0.011) | 0.042*** (0.009) | 0.028*** (0.005) |
| Controls | No | Yes | Yes |
| Fixed effects | No | No | Yes |
| Mean outcome | 0.52 | 0.52 | 0.52 |
| # observations | 38834 | 38834 | 38834 |
| # districts | 362 | 362 | 362 |

Notes: */**/** denotes significance at the 10/5/1 percent levels. Standard errors are clustered at the district level. Phone ownership is a binary variable equal to one if individuals self-reported owning a mobile phone at the time of the survey, and zero otherwise. Column (1) includes no controls or fixed effects. Column (2) adds individual-level controls for gender, age, income, and education. Column (3) adds the same controls and province by survey year fixed effects.

Table 3: First Stage: Mobile Towers and Lightning

| | Towers per 100,000 people |
|--------------------|---------------------------|
| Lightning (the IV) | -0.058*** (0.015) |
| Mean outcome | 2.31 |
| # observations | 53815 |
| # districts | 375 |

Notes: */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the district level. Lightning (the instrument) is measured as the maximum district-level lightning intensity observed between 1998 and 2013. Regression includes province by survey year fixed effects, as well as individual-level controls for age, gender, and ethnicity.

Table 4: The Effect of Mobile Phone Access on Attitudes Toward Women, OLS and IV Estimates

| | Education | | Employment | | Leadership | |
|---------------------------|---------------------|--------------------|---------------------|--------------------|-------------------|------------------|
| | OLS (1) | 2SLS (2) | OLS (3) | 2SLS (4) | OLS (5) | 2SLS (6) |
| Towers per 100,000 people | 0.008*** (0.002) | 0.018** (0.007) | 0.011*** (0.002) | 0.029** (0.012) | -0.001 (0.001) | 0.003 (0.006) |
| Mean outcome | 0.859 | 0.859 | 0.643 | 0.643 | 0.112 | 0.112 |
| Weak IV statistic | | 15.701 | | 15.701 | | 15.701 |
| # observations | 53815 | 53815 | 53815 | 53815 | 53815 | 53815 |
| # districts | 375 | 375 | 375 | 375 | 375 | 375 |

Notes: */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the district level. Outcome variables are binary indicators equal to 1 if the respondent agrees with women's education, employment, or leadership, respectively, and 0 otherwise. Lightning (the instrument) is measured as the maximum district-level lightning intensity observed between 1998 and 2013. All regressions include province by survey year fixed effects, as well as individual-level controls for age, gender, and ethnicity.

Table 5: The Effect of Mobile Phone Access on Attitudes Toward Women by Gender, IV Estimates

| | Education | | Employment | | Leadership | |
|---------------------------|--------------------|----------------------|--------------------|----------------------|--------------------|----------------------|
| | <i>Male</i> (1) | <i>Female</i> (2) | <i>Male</i> (3) | <i>Female</i> (4) | <i>Male</i> (5) | <i>Female</i> (6) |
| Towers per 100,000 people | 0.024** (0.009) | 0.005 (0.010) | 0.036** (0.015) | 0.015 (0.017) | -0.010 (0.006) | 0.031** (0.015) |
| Mean outcome | 0.814 | 0.919 | 0.527 | 0.794 | 0.087 | 0.145 |
| Weak IV statistic | 16.885 | 10.425 | 16.885 | 10.425 | 16.885 | 10.425 |
| # observations | 30399 | 23415 | 30399 | 23415 | 30399 | 23415 |
| # districts | 375 | 346 | 375 | 346 | 375 | 346 |

Notes: */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the district level. Outcome variables are binary indicators equal to 1 if the respondent agrees with women’s education, employment, or leadership, respectively, and 0 otherwise. Lightning (the instrument) is measured as the maximum district-level lightning intensity observed between 1998 and 2013. All regressions include province by survey year fixed effects, as well as individual-level controls for age, gender, and ethnicity.

Table 6: The Effect of Phone Towers on Attitudes Toward Women by Ethnicity, IV Estimates

| | Education | | Employment | | Leadership | |
|---------------------------|------------------------|----------------------|------------------------|----------------------|------------------------|----------------------|
| | <i>Pashtoon</i> (1) | <i>Others</i> (2) | <i>Pashtoon</i> (3) | <i>Others</i> (4) | <i>Pashtoon</i> (5) | <i>Others</i> (6) |
| Towers per 100,000 people | 0.015** (0.008) | 0.024* (0.013) | 0.018 (0.012) | 0.057** (0.024) | 0.002 (0.006) | 0.003 (0.011) |
| Mean outcome | 0.807 | 0.899 | 0.531 | 0.727 | 0.130 | 0.099 |
| Weak IV statistic | 12.395 | 7.464 | 12.395 | 7.464 | 12.395 | 7.464 |
| # observations | 23044 | 30748 | 23044 | 30748 | 23044 | 30748 |
| # districts | 303 | 311 | 303 | 311 | 303 | 311 |

Notes: */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the district level. Outcome variables are binary indicators equal to 1 if the respondent agrees with women’s education, employment, or leadership, respectively, and 0 otherwise. Pashtoon is the largest ethnic group in Afghanistan and Others include all non-Pashtoon. Lightning (the instrument) is measured as the maximum district-level lightning intensity observed between 1998 and 2013. All regressions include province by survey year fixed effects, as well as individual-level controls for age and gender.

Table 7: The Effect of Mobile Phone Access on Attitudes Toward Women, IV Estimates, Adding Baseline Covariates

| | Education | | Employment | | Leadership | |
|---------------------------------|--------------------|--------------------|--------------------|--------------------|------------------|------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Towers per 100,000 people | 0.019** (0.008) | 0.017** (0.008) | 0.026** (0.013) | 0.024** (0.012) | 0.002 (0.006) | 0.002 (0.006) |
| Mean outcome | 0.859 | 0.859 | 0.643 | 0.643 | 0.112 | 0.112 |
| Weak IV statistic | 12.986 | 13.890 | 12.986 | 13.890 | 12.986 | 13.890 |
| # observations | 53815 | 53815 | 53815 | 53815 | 53815 | 53815 |
| # districts | 375 | 375 | 375 | 375 | 375 | 375 |
| District-level controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Baseline controls \times Year | No | Yes | No | Yes | No | Yes |

Notes: All columns include the following district-level characteristics: elevation, log population (2010), share population with no education (2006), share population with primary education (2006), share Tajik (2006), share Hazara (2006), share other ethnic groups (2006), log reported income (2006), mean age (2006), share of female population (2006). “Baseline controls \times Year” interact all baseline characteristics with survey-year indicators to allow for differential trends across districts with different initial characteristics. */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the district level.

Table 8: Test of Exclusion Restriction – Reduced Form Conditional on Endogenous Variable

| | Education | | Employment | | Leadership | |
|---------------------------|----------------------|---------------------|----------------------|---------------------|-------------------|-------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Lightning (the IV) | -0.001*** (0.000) | -0.001 (0.000) | -0.002*** (0.001) | -0.001* (0.001) | -0.000 (0.000) | -0.000 (0.000) |
| Towers per 100,000 people | | 0.007*** (0.002) | | 0.011*** (0.002) | | -0.001 (0.001) |
| Mean outcome | 0.859 | 0.859 | 0.643 | 0.643 | 0.112 | 0.112 |
| F statistic | 39.242 | 34.554 | 121.529 | 99.114 | 60.580 | 45.942 |
| # observations | 53815 | 53815 | 53815 | 53815 | 53815 | 53815 |
| # districts | 375 | 375 | 375 | 375 | 375 | 375 |

Notes: */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the district level. Outcome variables are binary indicators equal to 1 if the respondent agrees with women’s education, employment, or leadership, respectively, and 0 otherwise. Lightning (the instrument) is measured as the maximum district-level lightning intensity observed between 1998 and 2013. All regressions include province by survey year fixed effects, as well as individual-level controls for age, gender, and ethnicity.

Table 9: Test of Exclusion Restriction – Reduced Form in Districts Without Towers

| | Education (1) | Employment (2) | Leadership (3) |
|--------------------|-------------------|-------------------|-------------------|
| Lightning (the IV) | -0.001 (0.001) | -0.001 (0.001) | -0.001 (0.001) |
| Mean outcome | 0.821 | 0.580 | 0.107 |
| F statistic | 31.070 | 96.704 | 19.669 |
| # observations | 15431 | 15431 | 15431 |
| # districts | 237 | 237 | 237 |

Notes: */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the district level. Data includes only districts that did not have any phone towers. Outcome variables are binary indicators equal to 1 if the respondent agrees with women's education, employment, or leadership, respectively, and 0 otherwise. Lightning (the instrument) is measured as the maximum district-level lightning intensity observed between 1998 and 2013. All regressions include province by survey year fixed effects, as well as individual-level controls for age, gender, and ethnicity.

Table 10: The Effect of Mobile Phone Access on Female Employment, IV Estimates

| | Women contribute to HH income (1) | Women contribution >25% of HH income (2) |
|---------------------------|---|--|
| Towers per 100,000 people | -0.002 (0.013) | 0.012** (0.006) |
| Mean outcome | 0.165 | 0.039 |
| Weak IV statistic | 8.821 | 10.425 |
| # observations | 14241 | 23415 |
| # districts | 292 | 346 |

Notes: */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the district level. In column (1), the outcome is a binary indicator equal to 1 if the respondent reports that women in the household contributed to household income and 0 otherwise. In column (2), the outcome is a binary indicator equal to 1 if women were reported to contribute more than 25% of household income. Difference in observations due to outcome in column 1 appearing in 2009-2013 survey years only while outcome in column 2 appears in 2006-2013 survey years. Lightning (the instrument) is measured as the maximum district-level lightning intensity observed between 1998 and 2013. All regressions include province by survey year fixed effects, as well as individual-level controls for age, gender, and ethnicity.

Table 11: The Effect of Mobile Phone Access on Attitudes Toward Women, Mediation Analysis

| | Mediator: Women Contribute more than 25% of Household Income | | |
|-----------------------|---|---------------------|-------------------|
| | Education (1) | Employment (2) | Leadership (3) |
| total effect | 0.018** (0.007) | 0.029** (0.012) | 0.003 (0.006) |
| direct effect | 0.008*** (0.002) | 0.011*** (0.002) | -0.001 (0.001) |
| indirect effect | 0.010 (0.008) | 0.018 (0.013) | 0.004 (0.006) |
| % mediation effect | 57.46 | 61.74 | 124.58 |
| F-statistic (T on Z) | 15.70 | 15.70 | 15.70 |
| F-static (M on Z T) | 6.66 | 6.66 | 6.66 |
| # observations | 53815 | 53815 | 53815 |
| # districts | 375 | 375 | 375 |

Notes: */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the district level. Estimates are based on the mediation framework of [Dippel et al. \(2019\)](#). Outcome variables are binary indicators equal to 1 if the respondent agrees with women’s education, employment, or leadership, respectively, and 0 otherwise. The mediator is a binary indicator equal to 1 if the respondent reports that women in the household contribute more than 25% of total household income, and 0 otherwise. Lightning (the instrument) is measured as the maximum district-level lightning intensity observed between 1998 and 2013. All regressions include province by survey year fixed effects, as well as individual-level controls for age, gender, and ethnicity.

Table 12: Downstream Effects of Mobile Phone Access on Female Education, IV estimates

| | No schooling (1) | Some high school (2) | Some university (3) | Current student (4) |
|--------------------------------|---------------------|-------------------------|------------------------|------------------------|
| Lag(Towers per 100,000 people) | -0.021 (0.020) | 0.019* (0.011) | 0.003* (0.002) | 0.025 (0.017) |
| Mean outcome | 0.613 | 0.124 | 0.011 | 0.149 |
| Weak IV statistic | 13.250 | 13.250 | 13.250 | 13.250 |
| # observations | 6563 | 6563 | 6563 | 6563 |
| # districts | 307 | 307 | 307 | 307 |

Notes: */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the district level. The data are aggregated at the district level. Column (1) reports the share of women with no formal schooling. Column (2) reports the share of women with some schooling below the primary level. Column (3) reports the share of women who completed primary education. Column (4) reports the mean years of schooling among women. Lightning (the instrument) is measured as the maximum district-level lightning intensity observed between 1998 and 2013. All regressions include the same controls as in [Table 4](#). Lag(Towers per 100,000 people) refers to the number of Roshan towers per 100,000 population in the district in the previous survey year

Table 13: Downstream Effects of Mobile Phone Access on Female Employment, IV estimates

| | Women working (1) | Women contribute to HH income (2) | Housewife (3) |
|--------------------------------|----------------------|---|-------------------|
| Lag(Towers per 100,000 people) | 0.003 (0.014) | 0.005 (0.006) | -0.028 (0.018) |
| Mean outcome | 0.172 | 0.054 | 0.769 |
| Weak IV statistic | 12.728 | 13.250 | 13.250 |
| # observations | 4590 | 6563 | 6563 |
| # districts | 281 | 307 | 307 |

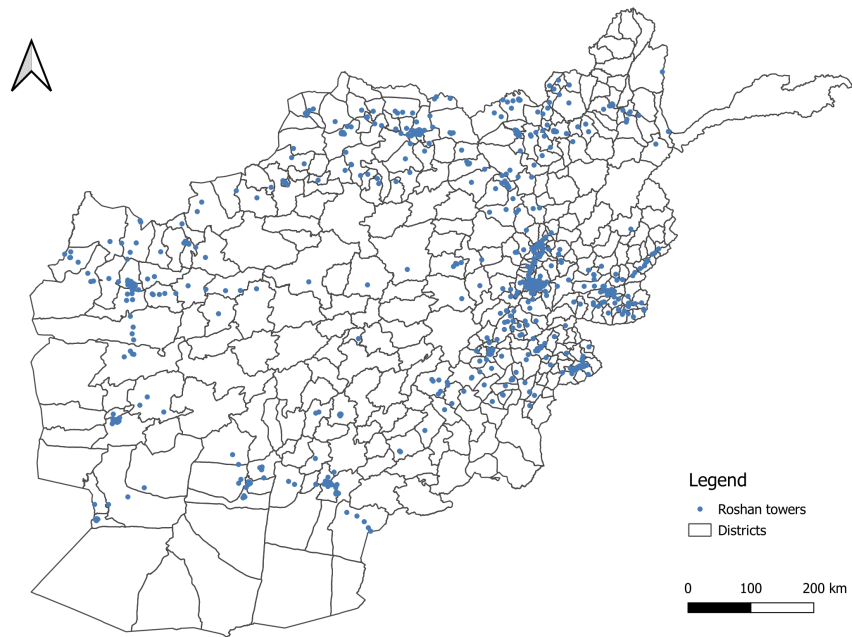
Notes: */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the district level. Column (1) reports the share of women with some form of employment. Column (2) reports the share of women who contribute to HH income through employment. Column (3) reports if woman in the household was a housewife. Lightning (the instrument) is measured as the maximum district-level lightning intensity observed between 1998 and 2013. All regressions include the same controls as in Table 4. Lag(Towers per 100,000 people) refers to the number of Roshan towers per 100,000 population in the district in the previous survey year. Difference in observations due to outcome in column 1 appearing in 2009-2013 survey years only while remaining outcomes appear in 2006-2013 survey years.

Table 14: Downstream Effects of Mobile Phone Access on Election Outcomes for Women, IV Estimates

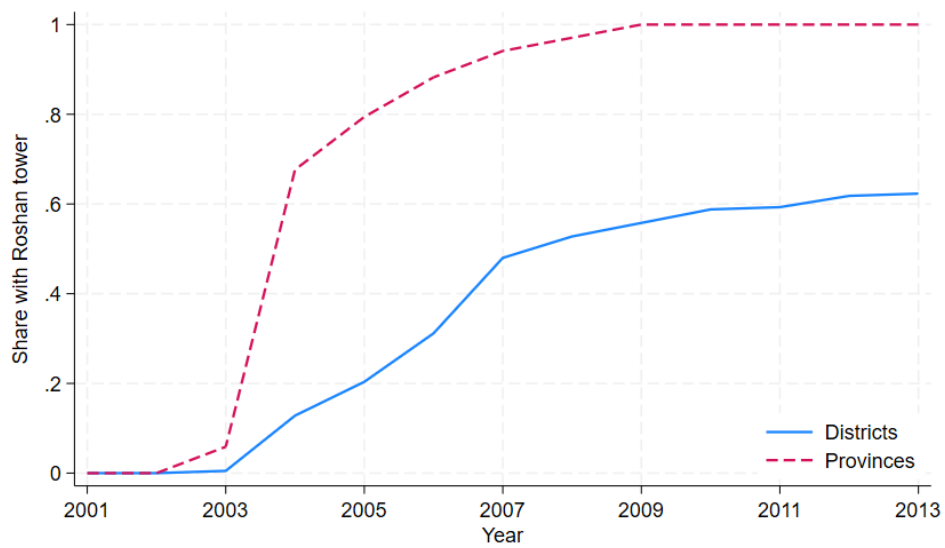
| | % Female candidates (1) | % Votes to Female candidates (2) | % Female candidates elected (3) |
|--------------------------------|----------------------------|--|---------------------------------------|
| Lag(Towers per 100,000 people) | 0.003 (0.002) | 0.010 (0.007) | 0.003 (0.003) |
| Mean outcome | 0.171 | 0.109 | 0.286 |
| Weak IV statistic | 5.331 | 5.603 | 5.331 |
| # observations | 547 | 546 | 547 |
| # districts | 329 | 329 | 329 |

Notes: */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the district level. Data is from Afghanistan's 2010 and 2018 parliamentary elections. Column (1) is the share of female candidates among all candidates in the district. Column (2) is the average share of votes cast to female candidates in the district. Column (3) is the share of female candidates elected to parliament in the district. Lightning (the instrument) is measured as the maximum district-level lightning intensity observed between 1998 and 2013. Lag(Towers per 100,000 people) refers to the number of Roshan towers per 100,000 population in the district in the survey year preceding the election.

(a) Roshan towers

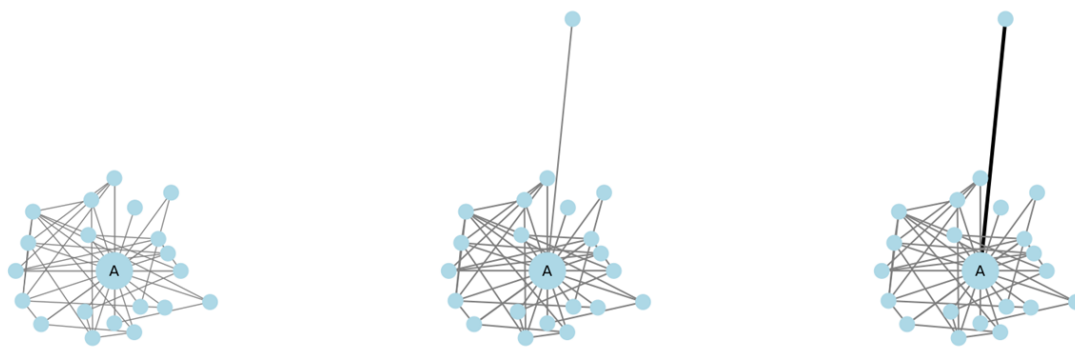


(b) Share of districts and provinces with at least one Roshan tower



Notes: Panel (a) depicts the location of Roshan towers over the sample period. Panel (b) shows the share of the 398 Afghan districts with at least one Roshan tower in the given year and the share of the 34 Afghan provinces with at least one Roshan tower in the given year.

Figure 1: Map and Time Series of Roshan Towers



(a) Pre-Phones Network

(b) Post-Phones Distant Tie

(c) Stronger Distant Tie

Figure 2: Sample Network before and after Mobile Phones

Notes: Panel (a) depicts a sample network for individual A prior to the advent of mobile phones. Panel (b) illustrates the formation of a new long-distance tie (e.g., a family member in Kabul) enabled by mobile connectivity. Panel (c) depicts a strengthening of that distant tie through increased interaction (e.g., phone calls, SMS).

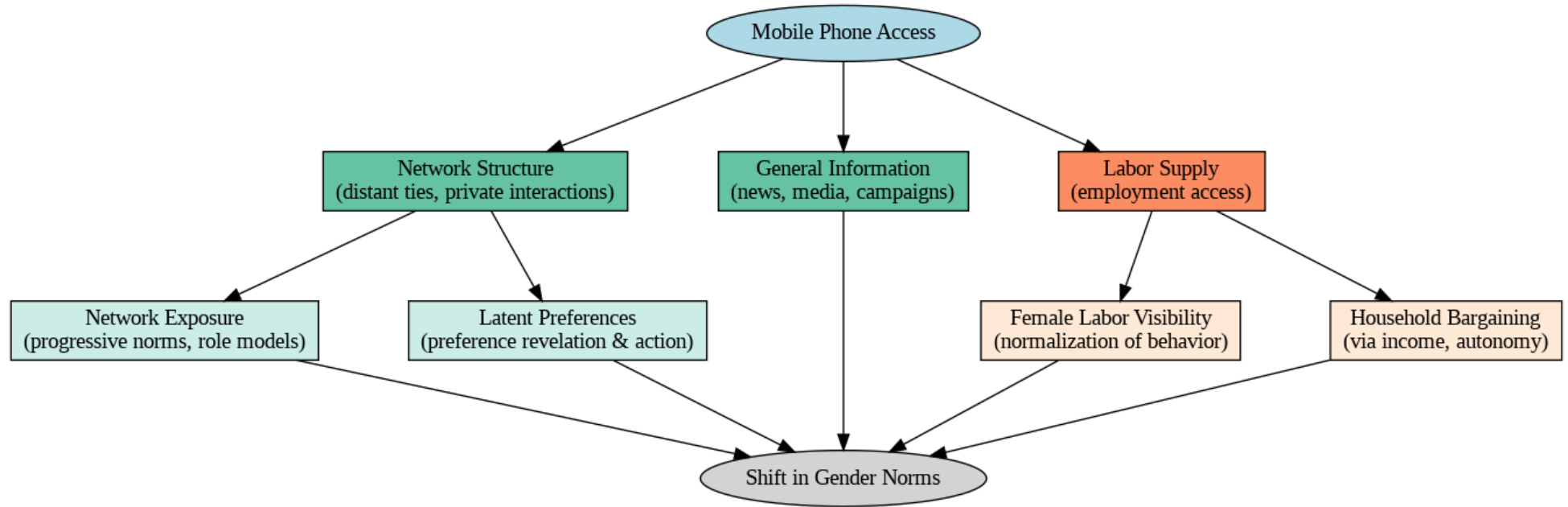
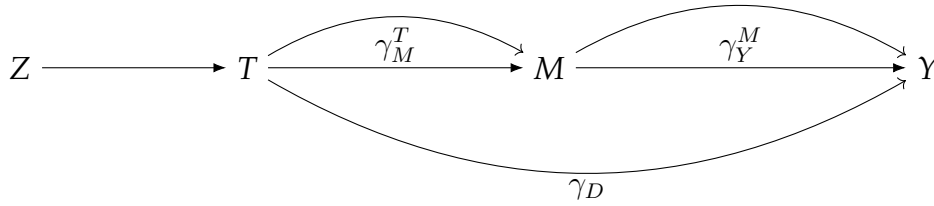


Figure 3: Mobile Phone Access and Gender Norms: Potential Mechanisms

Notes: Each box represents a mechanism/channel or subchannel. Dark green denotes the Information channel (both Network-dependent information and general information) while lighter shades of green denote specific information subchannels. Light shades of orange denote specific Labor Supply subchannels. Refer to section 6 for a detailed description of each mechanism

Figure 4: Mediation effect in DAG



Notes: This figure illustrates the IV mediation framework of [Dippel et al. \(2020\)](#). Z denotes the instrumental variable (lightning intensity), T represents mobile phone expansion (towers per 100,000 people), M is the mediator capturing female labor force participation or women's contribution to household income, and Y denotes attitudes toward women. The coefficient γ_D captures the direct effect of mobile phone expansion on gender norms, which we interpret primarily as the information channel. The indirect effect operates through the labor supply channel and is given by $\gamma_M^T \gamma_Y^M$, where γ_M^T measures the effect of mobile phone expansion on the mediator and γ_Y^M measures the effect of the mediator on attitudes toward women.

Appendix

A Tables

Table A1: Effects of Mobile Phone Access on Attitudes Toward Women – Number of Towers as IV

| | Education (1) | Employment (2) | Leadership (3) |
|-------------------|-------------------|-------------------|-------------------|
| Number of towers | 0.024** (0.01) | 0.039** (0.02) | 0.006 (0.01) |
| Mean outcome | 0.859 | 0.643 | 0.112 |
| Weak IV statistic | 6.636 | 6.636 | 6.636 |
| # observations | 53815 | 53815 | 53815 |
| # districts | 375 | 375 | 375 |

Notes: */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the district level. Outcome variables are binary indicators equal to 1 if the respondent agrees with women’s education, employment, or leadership, respectively, and 0 otherwise. Instead of towers per 100,000 people, the endogenous variable is number of towers. District population is directly used as a control variable. All regressions include province by survey year fixed effects, as well as individual-level controls for age, gender, and ethnicity.

Table A2: Effects of Mobile Phone Access on Attitudes Toward Women – Standard Errors Clustered at District Level

| | Education (1) | Employment (2) | Leadership (3) |
|--------------------------|-------------------|-------------------|-------------------|
| Towers per 10,000 people | 0.200** (0.09) | 0.339** (0.14) | 0.051 (0.05) |
| Mean outcome | 0.859 | 0.643 | 0.112 |
| Weak IV statistic | 13.124 | 13.124 | 13.096 |
| # observations | 53815 | 53815 | 53815 |
| # provinces | 34 | 34 | 34 |

Notes: */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the province level. Outcome variables are binary indicators equal to 1 if the respondent agrees with women’s education, employment, or leadership, respectively, and 0 otherwise. All regressions include province by survey year fixed effects, as well as individual-level controls for age, gender, and ethnicity.

Table A3: Effects of Mobile Phone Access on Attitudes Toward Women – Towers per Km^2 as IV

| | Education (1) | Employment (2) | Leadership (3) |
|-----------------------------|-------------------|-------------------|-------------------|
| Number of towers per km^2 | 1.605** (0.79) | 2.725** (1.32) | 0.428 (0.49) |
| Mean outcome | 0.859 | 0.642 | 0.113 |
| Weak IV statistic | 6.405 | 6.405 | 6.290 |
| # observations | 53320 | 53320 | 53320 |
| # districts | 372 | 372 | 372 |

Notes: */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the district level. Outcome variables are binary indicators equal to 1 if the respondent agrees with women’s education, employment, or leadership, respectively, and 0 otherwise. All regressions include province by survey year fixed effects, as well as individual-level controls for age, gender, and ethnicity.

Table A4: Effects of Mobile Phone Access on Attitudes Toward Women, with Probit Model

| | Education (1) | Employment (2) | Leadership (3) |
|--------------------------|--------------------|--------------------|-------------------|
| Towers per 10,000 people | 0.930*** (0.32) | 0.908*** (0.35) | 0.241 (0.31) |
| Mean outcome | 0.858 | 0.643 | 0.113 |
| # observations | 53486 | 53809 | 53488 |
| # districts | 369 | 369 | 369 |

Notes: All estimates are from probit IV model in Equation 2. */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the district level. Outcome variables are binary indicators equal to 1 if the respondent agrees with women’s education, employment, or leadership, respectively, and 0 otherwise. All regressions include province by survey year fixed effects, as well as individual-level controls for age, gender, and ethnicity.

Table A5: Effects of Mobile Phone Access on Attitudes Toward Women – Mean Lightning Instead of Maximum

| | Education (1) | Employment (2) | Leadership (3) |
|--------------------------|------------------|-------------------|-------------------|
| Towers per 10,000 people | 0.165* (0.09) | 0.156 (0.15) | 0.084 (0.07) |
| Mean outcome | 0.859 | 0.643 | 0.112 |
| Weak IV statistic | 9 | 9 | 9 |
| # observations | 53815 | 53815 | 53815 |
| # districts | 375 | 375 | 375 |

Notes: Instead of maximum lightning intensity during 1998-2013, mean lightning during that period is considered as IV in Equation 1. */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the district level. Outcome variables are binary indicators equal to 1 if the respondent agrees with women’s education, employment, or leadership, respectively, and 0 otherwise. All regressions include province by survey year fixed effects, as well as individual-level controls for age, gender, and ethnicity.

Table A6: Effects of Mobile Phone Access on Attitudes Toward Women – Accounting for Spillover Effects

| | Education (1) | Employment (2) | Leadership (3) |
|--------------------------|-------------------|-------------------|-------------------|
| Towers per 10,000 people | 0.221** (0.09) | 0.381** (0.16) | 0.015 (0.06) |
| Mean outcome | 0.862 | 0.651 | 0.112 |
| Weak IV statistic | 15.108 | 15.108 | 15.088 |
| # observations | 49182 | 49182 | 49182 |
| # districts | 361 | 361 | 361 |

Notes: Control districts adjacent to treatment districts are excluded to account for spillover effects. */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the district level. Outcome variables are binary indicators equal to 1 if the respondent agrees with women’s education, employment, or leadership, respectively, and 0 otherwise. All regressions include province by survey year fixed effects, as well as individual-level controls for age, gender, and ethnicity.

Table A7: Determinants of Mobile Phone Infrastructure Expansion Across Afghan Districts

| | Number of towers (2013) (1) | At least one tower (2013) (2) | Months to first tower (3) |
|-----------------------------------|--------------------------------|----------------------------------|------------------------------|
| Log district population | 4.484*** (1.103) | 0.261*** (0.048) | -23.776*** (4.141) |
| Log district area (sq. km) | -1.918** (0.880) | -0.037 (0.039) | 3.063 (3.340) |
| Mean elevation (m) | 0.002* (0.001) | -0.000*** (0.000) | 0.017*** (0.004) |
| District hospital in district | 6.337 (4.668) | -0.052 (0.061) | 4.589 (5.321) |
| Health subcenter in district | 6.539* (3.451) | -0.047 (0.040) | 3.804 (3.683) |
| Basic health facility in district | 2.102* (1.225) | -0.001 (0.032) | -0.563 (2.691) |
| Primary roads (km) | 0.039** (0.015) | 0.001 (0.001) | -0.095** (0.045) |
| Secondary road (km) | 0.009 (0.018) | 0.002** (0.001) | -0.233*** (0.079) |
| Tertiary road (km) | -0.001 (0.001) | -0.000 (0.000) | 0.006 (0.010) |
| Mean age | 0.132 (0.129) | -0.005 (0.006) | 0.340 (0.479) |
| Share with no education | -2.228 (2.542) | -0.078 (0.137) | 6.388 (11.558) |
| Share with primary education | 1.419 (6.499) | -0.262 (0.364) | 11.494 (28.474) |
| Share Tajik | -0.916 (2.466) | -0.059 (0.127) | -4.920 (10.049) |
| Share Hazara | 0.276 (2.281) | 0.125 (0.152) | -3.600 (13.773) |
| Share other ethnic groups | 2.483 (2.929) | 0.158 (0.150) | -11.212 (13.491) |
| Mean outcome | 3.022 | 0.559 | 48.728 |
| # observations | 313 | 313 | 313 |
| # districts | 313 | 313 | 313 |

Notes: Outcome in Column (1) is the number of mobile phone towers in the district by 2013 (end of sample), outcome in Column (2) is an indicator for whether there is any tower in the district by 2013, and outcome in Column (3) is the number of months before the arrival of the first tower in the district. Log district population is the natural logarithm of total district population. Log district area is the natural logarithm of district land area in square kilometers. District hospital, health subcenter, and basic health facility are indicator variables equal to one if the district contains at least one facility of the corresponding type. Primary roads, secondary roads, and tertiary roads measure the total kilometers within the district. Mean age, share with no education, share with primary education, share Tajik, share Hazara, and share other ethnic groups refer to the specified variable aggregated to the district level using the 2006 SAP responses. Road networks and health facilities are constructed using vector files collected by the Afghanistan Information Management Service (AIMS) and obtained through the Empirical Studies of Conflict Project ([Afghanistan Information Management Services , AIMS](#)). Elevation is derived from NASA's Shuttle Radar Topography Mission (SRTM30) ([National Aeronautics and Space Administration and National Geospatial-Intelligence Agency, 2000](#)). */**/** denotes significance at the 10/5/1 percent levels. Standard errors are clustered at the district level. All regressions include province fixed effects.

Table A8: The Effect of Mobile Phone Access on Attitudes Toward Women, IV Estimates, IV interacted with Survey Year

| | Education | | Employment | | Leadership | |
|---------------------------|--------------------|--------------------|--------------------|--------------------|------------------|------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Towers per 100,000 people | 0.018** (0.007) | 0.016** (0.006) | 0.029** (0.012) | 0.027** (0.011) | 0.003 (0.006) | 0.000 (0.005) |
| Mean outcome | 0.859 | 0.859 | 0.643 | 0.643 | 0.112 | 0.112 |
| Weak IV statistic | 15.701 | 3.117 | 15.701 | 3.117 | 15.701 | 3.117 |
| # observations | 53815 | 53815 | 53815 | 53815 | 53815 | 53815 |
| # districts | 375 | 375 | 375 | 375 | 375 | 375 |
| Year-specific first stage | No | Yes | No | Yes | No | Yes |

Notes: Columns with year-specific first stages instrument mobile phone infrastructure using interactions between lightning intensity and survey-year indicators. */**/** denotes significance at the 10/5/1 percent. Standard errors are clustered at the district level.

Table A9: The Effect of Mobile Phone Access on Attitudes Toward Women, Mediation Analysis

| | Mediator: Women's Contribution to Household Income | | | Mediator: Women Working | | |
|-----------------------|---|---------------------|-------------------|----------------------------|---------------------|-------------------|
| | Education | Employment | Leadership | Education | Employment | Leadership |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| total effect | 0.011 (0.007) | 0.013 (0.011) | -0.001 (0.006) | 0.011 (0.007) | 0.013 (0.011) | -0.001 (0.006) |
| direct effect | 0.008*** (0.002) | 0.011*** (0.002) | -0.002 (0.001) | 0.007*** (0.002) | 0.011*** (0.002) | -0.002 (0.002) |
| indirect effect | 0.003 (0.007) | 0.002 (0.011) | 0.001 (0.006) | 0.004 (0.015) | 0.002 (0.013) | 0.001 (0.007) |
| % mediation effect | 30.180 | 15.958 | -56.502 | 33.626 | 15.795 | -62.952 |
| F-statistic (T on Z) | 15.519 | 15.519 | 15.519 | 15.519 | 15.470 | 15.519 |
| F-static (M on Z T) | 6.309 | 6.309 | 6.309 | 0.157 | 0.127 | 0.157 |
| # observations | 35376 | 35376 | 35376 | 35376 | 35376 | 35376 |
| # districts | 371 | 371 | 371 | 371 | 371 | 371 |

Notes: *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. Standard errors are clustered at the district level. Estimates are based on the mediation framework of [Dippel et al. \(2019\)](#). Outcome variables are binary indicators equal to 1 if the respondent agrees with women's education, employment, or leadership, respectively, and 0 otherwise. The mediator in columns (1)–(3) is *Women's Contribution to Household Income*, a binary indicator equal to 1 if women contribute more than 25% of total household income, and 0 otherwise. The mediator in columns (4)–(6) is *Women Working*, a binary indicator equal to 1 if women in the household are engaged in income-generating activities. Lightning (the instrument) is measured as the maximum district-level lightning intensity observed between 1998 and 2013. All regressions include district and year fixed effects, as well as individual-level controls for age, gender, and ethnicity.