The Scandinavian
Journal of Economics

Scand. J. of Economics 113(2), 364–387, 2011
DOI: 10.1111/j.1467-9442.2010.01632.x

Income Inequality and Technology Diffusion: Evidence from Developing Countries*

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Abstract

We study the effect of within-country income inequality on the diffusion of mobile phones using data on market penetration in a sample of developing countries from 1985 to 1998. Mobile phones are an example of international technology, originating in industrialized countries and diffusing worldwide. We find that income inequality, as measured by the income share of the highest earning deciles, has a positive effect on the early diffusion of mobile phones and that the estimated effect becomes greater when a measure of agricultural endowments is used as an instrument. The instrumental variable results are robust to weak instruments. Our findings suggest that the diffusion of new technologies originating from industrialized countries may generate yet another channel that links inequality and development.

Keywords: Developing countries; inequality; mobile phones; technology diffusion; instrumental variables

JEL classification: *O*12; *O*33

I. Introduction

The rate of diffusion of mobile telephony has accelerated recently, and it has been estimated that there will soon be more than five billion mobile subscribers in the world. Mobile phones are an example of a technology that has emerged in the developed world, yet holds the potential to

*For comments, we thank a referee, seminar audiences in Berkeley, HECER, and Jyväskylä, Jenny and Peter Lanjouw, Matti Liski, Ted Miguel, Paul Stoneman, and Frank Verboven; for financial support, we thank the Yrjö Jahnsson and Ella and Georg Ehrnrooth Foundations and the Research Institute of the Finnish Economy–Berkeley Roundtable on the International Economy (ETLA–BRIE). We also thank the University of California at Berkeley for hospitality.

dramatically affect remote and less developed parts of the world.[1] Anecdotal and media accounts suggest that the diffusion of mobile telephony can result in technological catch-up and also that it is good for development.[2] What is unclear is how income inequality affects the early diffusion of modern technologies, particularly mobile phones, in the less developed parts of the world. For example, the recent extensive survey by Keller (2004) motivates the study of technology diffusion by income differences between countries, and by the potential of technology diffusion to narrow these, but it does not mention within-country income inequality. The objective of this paper is to study how variation in within-country inequality across developing countries affects the speed of diffusion of modern technology (originating in the industrialized parts of the world).

We focus on the effect of within-country inequality on the early diffusion of mobile phones by studying developing countries over a period prior to the end of the 1990s.[3] Mobile phones were relatively rare and expensive in the developing world at that time. Unlike today, it is highly unlikely that a representative consumer with mean (median) income could have afforded a mobile phone for consumption purposes only. This leaves us with two main reasons why within-country inequality might be directly related to the early diffusion of mobile phones. The first is that mobile phones are a consumption good that can be adopted (only) by the rich, high-earning elite.[4] Therefore, keeping the mean income constant and increasing the

[1] Another prominent example is medical technology. Its effects on health outcomes in countries that are not developers of medical technology have been analyzed in the interesting study by Papageorgiou *et al.* (2007). Eaton and Kortum (1999) have studied international technology diffusion more generally, using patent data.

[2] See, for example, *The Economist*, March 12, 2005: "Economic Focus: Calling across the Divide". Consistent with this, Röller and Waverman (2001) provide evidence that investments in telecommunications infrastructure have affected economic growth in developed (OECD) countries.

[3] The focus of the empirical literature to date differs from ours in two ways. First, a number of previous studies have analyzed how the diffusion of mobile telephony in developing countries differs from its diffusion in developed countries (see, for example, Rouvinen, 2006, and references therein). Second, we are aware of two papers that study technology diffusion and use a measure of income inequality. However, both of these focus on developed countries. Kiiski and Pohjola (2002) study the diffusion of the internet in the OECD countries. They use the Gini coefficient as an instrumental variable in their access cost equation, in which it obtains a positive and significant value. Tellis *et al.* (2003) study the takeoff of 137 new products in 16 European countries. The Gini coefficient is not significant in their estimations.

[4] The fruits of technological progress are not only better production goods that enhance productivity at work but also new (and improved) consumption goods. Mobile phones are a particularly interesting example of a new good that is both a production good and a consumption good and that apparently has had no near substitutes even in the developed countries (for a survey, see Hausman, 2002). In line with this, Hausman (1997), using US data, has estimated large consumer welfare effects from the introduction of mobile phones.

proportion of the rich (i.e., mass in the upper end of the income distribution) lead to a higher penetration rate. The obvious alternative explanation, suggested strongly in a number of anecdotal accounts, is that mobile phones are an important production good of the poor (see also the discussion in Röller and Waverman, 2001, and references therein).[5] If mobile phones are an especially useful production technology for the poor, then keeping the mean income constant and increasing the proportion of the poor (i.e., mass in the lower end of the income distribution) leads to a higher penetration rate. In either case, the shape of the income distribution and the early rates of diffusion of mobile phones are related.

It is important to note that we focus on the effect of within-country inequality on the early diffusion of mobile phones for a very specific reason. The hypotheses put forward above suggest that economies with more weight in the upper (or lower) tail of the income distribution will have higher penetration rates only initially. To see why, let us assume the absence of taste heterogeneity and imagine starting from a virtual price, the lowest price at which no individual adopts the new technology (Hausman, 1997), and then lowering the price by a small amount. The fatter the upper (lower) tail of the income distribution, the higher the number of rich (poor) individuals who will buy the new technology at the new price. With identical tastes, all individuals above (below) a certain income level will buy the new technology.[6] An important caveat to this prediction is that it only holds for the early stages of the diffusion path. Of two economies with the same mean income, the economy with a more even distribution of income must eventually have a higher penetration rate for some later portion of the diffusion path.[7] The converse is also true: if mobile phones were a more important consumption (production) good for the median or middle consumer than for the rich (the poor), economies with more weight in the upper (lower) tail of the income distribution would have lower penetration rates initially.

[5] See also Waverman *et al.* (2005), who report that mobile phone penetration correlates significantly with growth in developing countries.

[6] The assumption underlying the production argument is that, prior to the end of the 1990s, the poor of the developing countries could not afford a mobile phone for consumption purposes only. Building on this and anecdotal evidence, we put forward the hypothesis that the poor may have a stronger motive to adopt a mobile phone for production purposes than those with middle or median incomes. If this is true and if the poor become more numerous, more mobile phones will be sold—provided, of course, that the poor can directly or indirectly borrow against the income that the mobile-enabled production generates. This means that economies with more weight in the lower tail of the income distribution may have higher penetration rates initially.

[7] The reason is that if economy A's income distribution has more mass at both tails than the income distribution of economy B, its density crosses that of B first from above and then from below.

We find that income inequality, as measured by the income share of the highest earning deciles of the population, is directly related to the early diffusion of mobile phones. This result is robust to a number of misspecification and measurement problems. For example, it is robust to the endogeneity of within-country inequality, which could be a concern for a number of reasons. First, comparability and measurement problems are well known in the literature on inequality (see, for example, Easterly, 2007; Leigh, 2007, and references therein). They may lead to endogeneity and to a biased ordinary least-squares (OLS) estimate. Second, an omitted variables problem emerges if there are unobservables that correlate with both income inequality and technology diffusion. While we introduce a long vector of control variables to capture many, if not most, of the factors that previous studies have shown to affect the diffusion speed of mobile phones (e.g., demographics, demand factors, market structure, existing telecommunications infrastucture, etc.), the possibility of having important unobservables remains. For example, we cannot observe the preferences that determine the primary ways in which people use mobile phones in developing countries. They are, therefore, a component of the error term. Third, simultaneity bias could also arise if inequality and diffusion are jointly determined.

Our point estimate of the effect of the income share of the highest earning deciles on diffusion increases significantly when a measure of factor (agricultural) endowments is used as an instrument. The instrument comes from Easterly (2007) and exploits exogenous variation in inequality, which is a result of regional variation in the suitability of land for growing wheat (versus sugar cane). This variation predicts inequality in our sample of developing countries in the same way as it does in the larger sample studied by Easterly (2007). Moreover, we show that the instrumental variable (IV) estimates are not sensitive to the problem of weak instruments (see, for example, Andrews and Stock, 2005) or to relaxing the exclusion restriction locally (see Conley *et al.*, 2008).

The result that the income share of the highest earning deciles is directly related to the diffusion of mobile phones is also robust to introducing a measure of the income share of the lowest earning deciles to the diffusion model. These two measures of inequality are strongly negatively correlated, but they both obtain positive coefficients, which are jointly significant in the OLS estimations. We obtain additional instruments from Easterly (2001) and Isham *et al.* (2005) and show that IV estimations with two endogenous inequality variables echo these OLS results.

The remainder of this paper is organized as follows. In the next section, we describe our data sources. In Section III we present our econometric model, and in Section IV we present the empirical results and analyses of robustness. In Section V, we offer brief conclusions.

II. The Data

The data used in this paper come from several sources. The mobile phone data—penetration rates, technologies in use (analog and digital), number of firms, use of so-called prepaid cards, and the concentration ratio—come from the standard source of international mobile phone data, the EMC (see http://www.wcisdata.com/). The country characteristics are from the World Development Indicators (WDI), the legal origin variables are from La Porta *et al.* (1997), and the political and civil rights variables from Freedom House (2002). The data on income inequality (income shares of the highest and lowest earning deciles and the Gini coefficients) come from the World Income Inequality Database (WIID) of the World Institute for Development Economics Research (WIDER, 2000). Finally, the data for the main IV (the amount of land suitable for growing wheat relative to that suitable for growing sugar cane) are from Easterly (2007, Appendix A). Our alternative instruments, discussed below, come from Easterly (2001) and Isham *et al.* (2005).

The availability of data in the early stages of the diffusion of mobile technology and the measures of income inequality effectively determine the sample we use. The EMC data give us the relevant variables for all years for which a mobile phone network has existed in a given country. The dataset covers all the countries that have introduced mobile phones, providing us with data over the early stages of the diffusion of mobile technology in the less developed parts of the world. The most limiting source of data from our perspective is the WIID, in terms of both quantity and, potentially, quality. Quantity-wise, unlike the other data (with the exception of the legal origin variables, which naturally are a cross-section), it does not form a complete panel. Quality-wise, Atkinson and Brandolini (2001) note several difficulties in using secondary datasets, and emphasize the difficulties related to inequality measures, in particular, the Gini coefficient.

The final estimation sample consists of 48 developing countries. The number of country–year observations in the (estimation) sample is 289, and the number of observations per country depends on when the first mobile phone network was opened. In the estimation sample, the opening year varies from 1985 (e.g., Tunisia) to 1997 (e.g., Mali). The sample available to us ends in 1998.

III. The Econometric Model

The Model

There are two standard approaches in the large body of literature on new technology diffusion. The first is to model the diffusion speed—see Gruber and Verboven (2001) and Liikanen *et al.* (2004) for examples on mobile phones—of the new technology. The second is to model the penetration rate of the new technology (see, for example, Caselli and Coleman, 2001). We follow the latter approach and consider models of the following form:

$$\log(Penrate_{it}) = \alpha + \delta \times \log(Ineq_{it}) + X_{it}beta + \varepsilon_{it}. \quad (1)$$

Here, $Penrate_{it}$ refers to the penetration rate of mobile phones at time t for country i, $Ineq_{it}$ is a measure of within-country inequality, X_{it} denotes a vector of control variables (with the associated parameter vector β), and ε_{it} is the error term. The main interest is in δ, which is the parameter characterizing the effect of within-country inequality on the penetration rate of mobile phones. We use logarithmic transformations of all the continuous control variables.

We estimate equation (1) under two different assumptions about the error term. First, we assume that $E[\varepsilon_{it}|X_{it}, \log(Ineq_{it})] = 0$ and estimate the model using OLS. Second, we acknowledge that the assumption may be compromised and we use IV methods that allow for the endogeneity of the inequality measures, that is, $corr[\varepsilon_{it}, \log(Ineq_{it}) \neq 0]$ (see the discussion in subsection “Endogeneity and Instruments”).

We always allow for heteroskedasticity and within-country clustering when estimating the standard errors.

Measures of Inequality

We use the income share of the highest earning deciles as our primary measure of inequality. This choice is motivated by the observation that the income share of the highest earning deciles is, at least potentially, more reliably measured, and therefore less prone to measurement error, than a Gini coefficient. We also obtain a larger sample using the top income share instead of the Gini coefficient. Leigh (2007) reports that the top income share is highly correlated with other measures of inequality and suggests its use when other measures are of low quality or unavailable. To err on the conservative side, we only use those income decile data that the WIDER denotes as high quality and that are measured consistently over years and countries.

We use three different measures of the highest earning deciles: the income shares of the top four ($Incshare80100_{it}$) and two ($Incshare100_{it}$) deciles (i.e., the combined share of the highest two quantiles and that of the highest quantile) as well as the earnings share of the richest decile (10 percent) of the population ($Incshare90100_{it}$). As a measure of the earnings share of the poor, we use the income share of the lowest two income deciles ($Incshare20_{it}$).

The theoretical reason that income inequality might be positively related to the early rates of penetration refers to the share of rich (or poor) in the population, not to the income share of a given number of rich (poor) people *per se*. Our analysis builds on the assumption that the inequality measures available to us are positively correlated with the tail masses of the income distribution. To demonstrate the fact that our results are robust to this and other sources of measurement error, we use an alternative measure of inequality (the Gini coefficient, $Gini_{it}$) and an IV approach.[8]

For many countries in our data, there is just one value for the income variable; for others, there are more. We have opted to always use the latest measure of the income shares, with the proviso that if there are several values (measured in different years) for a given country, we use for year t the value that has been measured prior to year t, if such a value is available. Otherwise, we use the value that has been measured in the year closest to year t. The empirical model we estimate includes controls for the measurement error that this infrequent measurement of inequality potentially induces.

Control Variables

We have five groups of control variables that comprise X_{it}. The first group consists of country observables; it includes (the log of) GDP per capita ($Gdpcap_{it}$) to control for mean income. We predict this to have a positive effect on the penetration rate. To control for differences in demographics and tastes, we include the size of the population (Pop_{it}), the ratio of population to the size of the geographical area ($Dens_{it}$), the proportions of the urban ($Urban_{it}$) and female ($Popf_{it}$) populations and the age-dependency ratio ($Agedep_{it}$) in the estimation. These have been shown in previous studies to affect the speed of diffusion of mobile phones. We include latitude ($Latit_i$) to control for differences in climate; this is especially relevant with respect to the exogeneity of our instruments (see below).

The second group consists of variables that might be called industry observables. One of the most important variables belonging to this group is the penetration rate of fixed-line phones. Holding other country characteristics constant, this variable should be highly correlated with the quality of the existing (e.g., fixed-line) telecommunication infrastructure ($Telm_{it}$). To further control for the current state of the telecommunications infrastructure and markets, we include the number of mobile phone operators ($Licenses_{it}$) and the Herfindahl index of mobile phone markets ($Hhi3_{it}$). These variables correlate with operator market power. They indirectly control for handset and call prices, for example, as in most countries, handsets are sold by

[8] In regressions that use the Gini coefficient, we have to use a smaller estimation sample.

mobile phone operators who bundle them with service (call) contracts. We also include a dummy if prepaid cards are in use in country i in year t ($Prepaid_{it}$), and similarly a dummy for the existence of a second generation digital mobile phone network ($Digid_{it}$). The switch from first generation analog phones to second generation digital phones constituted a discrete change in the quality of mobile telecommunications. As telecommunications is a regulated industry, we additionally include variables that have been used to explain the (government) decision to adopt a first generation (analog) mobile phone network: the legal origin of the country ($Socialist_i$ and $French_i$ dummies), and the country's political and civil rights ($Polciv_{it}$). These may affect, through political economy mechanisms, the regulatory regime of the industry, and thereby also the quality and pricing of past and current telecommunications services.

A challenge in any diffusion study is to control for changes in the quality of the good, and in the marginal cost of producing it. The third group of control variables consists, therefore, of calendar year dummies. Conditional on the control variables described above, calendar year dummies should control for (common) technical progress over a given period. They also capture any (unobservable) trends affecting the diffusion of mobile phones to the extent that such trends are global. Furthermore, the inclusion of calendar year dummies controls for any systematic variation in the year of introducing mobile phones in a given country that may be driven by income inequality. In other words, conditional on the calendar year dummies, it is as if the introduction of mobile phones into our sample countries were random.

The fourth group of control variables consists of diffusion year dummies. There are many reasons for including these. There may be post-launch learning by doing, which will affect prices and thereby penetration rates. Furthermore, if diffusion is constrained by lack of information about the new good (the epidemic model) or is an outcome of consumer herding or information cascades, diffusion year dummies capture the early stages of this common pattern. Diffusion year dummies can also control for any explanation (beyond the epidemic or cascade models) that might give rise to the widely documented S-shaped diffusion path (see, for example, Geroski, 2000, who discusses such explanations in detail).

The final group of control variables to be included in X_{it} is related to our measures of income inequality. As explained above, the income share of the highest earning deciles is measured a different number of times in different countries, and in different years. Even after choosing to use only household-level income measures that are denoted "high quality" by the WIDER, potential measurement problems continue to exist. We control for these first by introducing a vector of year-of-measurement dummies that take the value one in any year if the income variable used for that country–year observation has been measured in year t. These year-of-measurement dummies capture, for example, the measurement error that is a result of (worldwide) changes in the calculation of the income share of the highest earning decile. Our qualitative results are robust to using an alternative control for potential measurement errors in income inequality, to not controlling for them at all and to using an IV estimator.

Endogeneity and Instruments

The endogeneity of the inequality measures, that is, $corr[\varepsilon_{it}, \log(Ineq_{it}) \neq 0]$, is a concern to us. First, the measurement problems to which we have already referred may lead to a (downward) biased OLS estimate. Second, while our explanatory variables control for many of the factors that have been shown by previous studies to affect the speed of diffusion of mobile phones, we cannot observe, for example, the preferences that determine the primary way in which people use mobile phones in developing countries. This may lead to an omitted variables problem. Third, simultaneity bias arises if inequality and diffusion are jointly determined. While we are not aware of a formal model that would result in such an equilibrium, earlier research suggests two reasons why this possibility should not be ignored. On the one hand, it has been suggested that technology diffusion may lead to income convergence, at least between countries (see, for example, Detragiache, 1998). On the other hand, income inequality reflects both structural and market inequality (Easterly, 2007). The former reflects how non-market forces, such as conquest, colonization, distribution of land by the colonial power, and other historical (political economy) events contribute to the creation of economic elites and (structural) income inequality. The latter reflects, in contrast, inequality that is market-induced (i.e., a result of uneven market outcomes across individuals). If the penetration of mobile phones results in either more or less even market outcomes, the component of inequality that is market-induced may be jointly determined with the rate of penetration.

Our main IV, regional variation in the suitability of land for growing wheat (versus sugar cane), is a measure of factor endowments. The measure we adopt from Easterly (2007) is $Lwheatsugar_i = \log[(1 +$ arable land suitable for wheat$)/(1 +$ arable land suitable for sugar cane$)]$ in country i and it is originally from the Food and Agriculture Organization (FAO). It is a relevant instrument, if, as a large literature suggests, agricultural endowments are a key driver of (structural) inequality (see Easterly, 2007, p. 756, and the numerous papers cited therein). The better the land endowments of a geographical region lend themselves to commodities and products whose production process featured economies of scale and allowed the use of slave labour, the larger the scope for (structural) inequality. As Easterly demonstrates, this instrument works as predicted by the prior literature, making use of variation in factor endowments; the regional variation in $Lwheatsugar_i$ has considerable predictive power for inequality. It also turns out that there is considerable variation within both tropical and non-tropical areas in this measure and that it can predict domination of landownership by family firms, which can be regarded as a measure of (past) inequality.

Regional variation in the suitability of land for growing wheat is exogenous if, conditional on the control variables included, it does not affect the diffusion of mobile phones other than via its effect on inequality (i.e., if it is not correlated with the unobservables influencing the diffusion of mobile phones). *A priori* reasoning can rarely be conclusive, but we think that the instrument is plausibly exogenous because it is associated with structural rather than market inequality. This reduces the likelihood that technology diffusion, which may lead to income convergence (or divergence), makes the instrument endogenous. The instrument is plausibly exogenous also because, conditional on the quality of existing telecommunications services (i.e., the penetration rate of fixed-line phones and other industry observables) and country characteristics (such as latitude and the proportion of the urban population), it is difficult to see why $Lwheatsugar_i$ should have a direct effect on the diffusion of mobile phones.

Our alternative instruments come from Easterly (2001) and Isham *et al.* (2005). From the former, we obtain an indicator for point-source commodity exporters, $Pointsource_i$. This variable correlates with the propensity that a country suffers from a sort of "resource curse", because certain types of commodity windfalls seem to lead to bad political institutions and uneven economic outcomes (for a review, see Isham *et al.*, 2005). We use $Pointsource_i$ to identify countries that produce and export mostly goods (e.g., coffee, oil, sugar cane) that are typically controlled by a privileged minority and that easily lead to a (further) concentration of income and wealth. This means that $Pointsource_i$ is regarded as a determinant of structural inequality. Following Easterly (2001), we construct a second alternative instrument for inequality by isolating countries with a tropical location. The variable, $Latdum_i$, is a dummy that takes the value one if the country's mean absolute latitude is less than 23.5°, and zero otherwise. Using this dummy as an instrument for inequality is consistent with the literature, arguing that in the tropics, there is (for various historical and political reasons) a rich elite that has for centuries maintained its status by adopting "extractive strategies" (see, for example, Easterly, 2001, 2007, and references therein). Conditional on the country observables (including latitude), $Latdum_i$ is therefore a determinant of structural inequality.

The alternative instruments are not ideal, but we use them for two purposes. First, they serve as instruments for the lowest earning deciles in regressions with two endogenous inequality variables. Second, they allow us to implement a test of the exogeneity of the main instrument, $Lwheatsugar_i$.

The validity of instruments is difficult to establish. We therefore also consider the robustness of our IV inference to the problem of weak instruments (for a review, see, for example, Andrews and Stock, 2005) and to relaxing the exclusion restriction (following Conley *et al.*, 2011).

IV. Empirical Results

Descriptive Statistics

Table 1 presents descriptive statistics for the estimation sample. The rate of penetration of mobile phones, $Penrate_{it}$, is measured by the ratio of mobile subscribers ($\times 100$) to population at time t for country i. The mean penetration rate is low, reflecting the fact that the sample consists of developing countries and that the penetration data cover the early phases of the diffusion path. At the end of the sample, it is only 1.9 percent. The mean gross domestic product per capita in our sample (purchasing power parity [PPP] figures from the WDI) is \$3,700, with a relatively high variance.

Table 1. *Descriptive statistics*

Variable	Mean	S.D.
Penetration rate (%) [$Penrate_{it}$]	0.655	1.710
Population [Pop_{it}]	4.61E07	1.15E08
Population density [$Dens_{it}$]	100.256	137.81
Proportion of urban population (%) [$Urban_{it}$]	45.753	19.515
GDP per capita (PPP \$) [$Gdpcap_{it}$]	3,704.718	2,315.539
Main telephone lines (per 000) [$Telm_{it}$]	75.296	89.157
Proportion of females (%) [$Popf_{it}$]	50.440	1.316
Age dependency ratio [$Agedep_{it}$]	0.700	0.154
Political and civil rights [$Polciv_{it}$]	0.578	0.229
French legal origin [$French_i$]	0.370	0.483
Socialist legal origin [$Socialist_i$]	0.277	0.448
Number of telecom operators [$Licences_{it}$]	1.884	1.224
Herfindahl index [$Hhi3_{it}$]	7,668.88	2,842.90
Prepaid [$Prepaid_{it}$]	0.097	0.296
Digital [$Digid_{it}$]	0.422	0.494
Income share of highest earning decile (%) [$Incshare90100_{it}$]	31.335	6.781
Income share of highest earning quintile (%) [$Incshare100_{it}$]	46.883	7.247
Income share of the two highest earning quintiles (%) [$Incshare80100_{it}$]	68.883	6.151
Income share of lowest earning quintile (%) [$Incshare20_{it}$]	6.606	1.949
Agricultural endowments [$Lwheatsugar_i$]	0.056	0.163
Latitude [$Latit_i$]	0.278	0.184

Notes: This table presents descriptive statistics for the estimating sample used in the main analysis of the paper. The sample is an unbalanced panel that covers 48 countries and the years 1985–1998, totaling 289 country–year observations. The Herfindahl index has been scaled on [0, 10, 000].

The means of the income share of the top four ($Incshare80100_{it}$) and two ($Incshare100_{it}$) deciles are 68.8 and 46.9 percent, respectively, whereas the mean of the income share of the richest decile ($Incshare90100_{it}$) is 31.3 percent. The mean of the income share of the lowest two income deciles ($Incshare20_{it}$) is 6.6 percent.

The correlation coefficient between log($Penrate_{it}$) and log($Gdpcap_{it}$) is 0.80 using the 1998 cross-section (p-value < 0.01). In the whole estimation sample, the correlation is 0.48 (p-value < 0.01). These numbers show that mean income and the penetration rate are positively correlated in the raw data.

In line with Easterly (2007), we find that $Lwheatsugar_i$ is negatively associated with the income share of the highest earning deciles. For example, its correlation with $Incshare80100_{it}$ is -0.27 and highly significant. $Pointsource_i$ and $Latdum_i$ correlate positively with the income share of the highest earning deciles, as expected.

Basic OLS and IV Results

The Highest Earning Deciles as a Measure of Inequality. The first set of estimation results, presented in columns 1–3 of Table 2, are based on OLS estimations with heteroskedasticity- and cluster-robust standard errors. In all columns, the inequality measure is (log of) $Incshare80100_{it}$. In column 1, we include only the first group of control variables (i.e., country observables). In column 2, we add the calendar and diffusion year dummies. In column 3, we augment the specification of column 2 with the industry observables.

The results are consistent across the table; in each column, the coefficient of the inequality measure is positive and significant at better than the 1 percent confidence level. These elasticities indicate that at least during the early stages of the diffusion path, on which we focus, the more weight there is in the upper tail of the income distribution, the higher the mobile phone penetration rate. Focusing on column 3, we find that no group of control variables is redundant; the country and industry characteristics, the calendar year dummies and the diffusion year dummies are each jointly highly significant as a group. Only a few of the individual control variables are significant, however. Population and the age-dependency ratio affect the penetration rate negatively, whereas the number of licenses and prepaid (and, marginally, digital) dummies have a positive effect on diffusion. Interestingly, (the log of) $Gdpcap_{it}$ obtains a positive but insignificant coefficient.

The second set of estimation results, presented in columns 1–3 of Table 3, shows that the OLS results do not depend on either the year of measurement or choice of the inequality measure. In column 1, we augment

Table 2. *OLS estimation results*

Variable	1 $Incshare80100_{it}$	2 $Incshare80100_{it}$	3 $Incshare80100_{it}$
$Inequality_{it}$	6.067*** (2.107)	6.486*** (2.067)	5.450*** (1.685)
Pop_{it}	−0.216 (0.145)	−0.299** (0.139)	−0.478*** (0.142)
$Dens_{it}$	0.383*** (0.137)	0.396** (0.154)	0.269** (0.130)
$Urban_{it}$	0.861* (0.450)	0.429 (0.483)	0.121 (0.516)
$Gdpcap_{it}$	−0.056 (0.481)	0.622 (0.494)	0.701 (0.474)
$Popf_{it}$	9.390 (8.735)	−0.468 (6.959)	−1.761 (6.777)
$Agedep_{it}$	−5.243*** (1.344)	−3.364** (1.315)	−1.299 (1.200)
$Latit_i$	−0.212 (0.226)	−0.017 (0.197)	0.095 (0.144)
$Telm_{it}$			0.158 (0.211)
$Licenses_{it}$			0.401*** (0.083)
$Hhi3_{it}$			−0.474 (0.293)
$Prepaid_{it}$			0.572** (0.265)
$Digid_{it}$			0.154 (0.267)
$Polciv_{it}$			−0.570 (0.342)
$Socialist_i$			0.072 (0.444)
$French_i$			0.338 (0.307)
Calendar year dummies	No	Yes	Yes
Diffusion year dummies	No	Yes	Yes
N_{obs}	289	289	289
R^2	0.366	0.768	0.829
T1	0.000	0.000	0.000
T2	–	0.000	0.000
T3	–	0.000	0.000

Notes: This table reports the OLS estimations of the model for mobile phone diffusion. In all columns, the dependent variable is the penetration rate and inequality is measured by the income share of the top four deciles. In column 1, control variables include country observables, in column 2 they also include calendar and diffusion year dummies and, in column 3, the model is further augmented by industry observables. For precise definitions of the included variables, see Table 1 and the second and third subsections of Section III. The numbers presented are coefficients and standard errors (in parentheses). Standard errors are clustered at country level. ***, **, * denote significance at the 1%, 5%, 10% level, respectively. T1 is the joint significance of the explanatory variables bar the two sets of year dummies (*p*-value). T2 is the joint significance of diffusion year dummies (*p*-value). T3 is the joint significance of calendar year dummies (*p*-value).

the most complete specification (column 3) of Table 2 by the year-of-measurement dummies. In columns 2 and 3, we repeat this estimation, but using alternative measures of inequality. In column 2, it is (log of) $Incshare100_{it}$ whereas in column 3 the measure is (log of) $Incshare90100_{it}$. For brevity, we only display the estimated coefficients of the inequality measures. In each column, the coefficient of the inequality measure is positive and significant at better than the 5 percent confidence level. The year-of-measurement dummies are jointly significant in each column.

Table 4 presents the results of the IV estimations that use the agricultural endowment, $Lwheatsugar_i$, as an instrument for the measures of inequality. The specifications correspond to those of Table 3. We use the two-stage least-squares (2SLS) estimator and allow the error terms to be heteroskedastic and clustered at the country level.

Table 3. *OLS estimation results*

Variable	1 $Incshare80100_{it}$	2 $Incshare100_{it}$	3 $Incshare90100_{it}$
Inequality	5.720*** (1.779)	3.398*** (1.037)	2.095*** (0.735)
Control variables	Yes	Yes	Yes
Calendar year dummies	Yes	Yes	Yes
Diffusion year dummies	Yes	Yes	Yes
Measurement year dummies	Yes	Yes	Yes
N_{obs}	289	289	289
R^2	0.851	0.852	0.848
T1	0.000	0.000	0.009
T2	0.000	0.002	0.000
T3	0.000	0.000	0.000
T4	0.000	0.002	0.000

Notes: This table reports the OLS estimations of the model for mobile phone diffusion in which the dependent variable is the penetration rate and control variables include country observables, calendar and diffusion year dummies and industry observables (i.e., the model reported in column 3 of Table 2), augmented or varied as follows. In column 1, the model is augmented by the year-of-measurement dummies and inequality is measured by the income share of the top four deciles. In column 2, we use the same specification as in column 1, but measure inequality by the income share of the top two deciles. In column 3, we use the same specification as in column 1, but measure inequality by the income share of the top decile. Column headings refer to these three different measures. We present the coefficients and standard errors (in parentheses), but only for the inequality measures, which are the main variables of interest. Standard errors are clustered at country level. ***, **, * denote significance at the 1%, 5%, 10% level, respectively. T1 is the joint significance of the explanatory variables bar the two sets of year dummies (p-value). T2 is the joint significance of diffusion year dummies (p-value). T3 is the joint significance of calendar year dummies (p-value) and T4 is the joint significance of year-of-measurement dummies (p-value).

As the table shows, the IV estimates of the coefficient of inequality are clearly greater than the corresponding OLS estimates. The coefficients of the inequality measures are significant at better than the 5 percent level in the first two columns. While large and positive, the corresponding coefficient in column 3 has a p-value of 0.116. Taken together, these elasticities support the view that the more mass there is in the upper tail of the income distribution, the higher the mobile phone penetration rate.

We consider the validity of $Lwheatsugar_i$ as an instrument for the inequality measures in detail in a separate analysis of robustness (see below). To anticipate, these IV results are qualitatively robust to weak instruments and to relaxing the exclusion restriction locally.

The Highest and Lowest Earning Deciles as a Measure of Inequality. As discussed earlier, within-country inequality may affect the early diffusion of mobile phones for two reasons. First, if mobile phones are a consumption good that can be adopted only by the rich elite, increasing the proportion of the rich ought to lead to a higher penetration rate. Second, if mobile phones are a useful production technology for the poor, increasing the proportion of the poor ought to lead to a higher penetration rate.

Table 4. *IV estimation results*

Variable	1 $Incshare80100_{it}$		2 $Incshare100_{it}$		3 $Incshare90100_{it}$	
$Inequality_{it}$	25.394**	(11.026)	14.658**	(5.939)	14.770	(9.410)
Pop_{it}	−0.604***	(0.155)	−0.611***	(0.147)	−0.621***	(0.208)
$Dens_{it}$	0.754*	(0.403)	0.704*	(0.365)	1.142	(0.855)
$Urban_{it}$	1.458*	(0.840)	1.629*	(0.904)	2.006	(1.570)
$Gdpcap_{it}$	−0.300	(0.734)	−0.466	(0.763)	−0.100	(0.941)
$Popf_{it}$	−26.587	(17.964)	−25.995	(16.714)	−33.436	(29.857)
$Agedep_{it}$	−8.960***	(2.955)	−8.898***	(2.908)	−9.116**	(4.562)
$Latit_i$	0.356*	(0.200)	0.381*	(0.200)	0.472	(0.315)
$Telm_{it}$	−0.568	(0.446)	−0.511	(0.435)	−0.657	(0.735)
$Licenses_{it}$	0.055	(0.224)	0.060	(0.216)	−0.144	(0.457)
$Hhi3_{it}$	−0.378	(0.239)	−0.338	(0.240)	−0.418	(0.345)
$Prepaid_{it}$	0.916**	(0.391)	0.882**	(0.379)	0.776*	(0.456)
$Digid_{it}$	0.455	(0.383)	0.346	(0.354)	0.241	(0.457)
$Polciv_{it}$	0.194	(0.553)	0.146	(0.537)	0.313	(0.780)
$Socialist_i$	2.061	(1.641)	2.006	(1.530)	3.683	(3.444)
$French_i$	0.638	(0.554)	0.674	(0.571)	0.587	(0.857)
Calendar year dummies	Yes		Yes		Yes	
Diffusion year dummies	Yes		Yes		Yes	
Measurement year dummies	Yes		Yes		Yes	
N_{obs}	289		289		289	
T1	0.000		0.000		0.268	
T2	0.000		0.002		0.000	
T3	0.000		0.000		0.000	
T4	0.000		0.001		0.000	

Notes: This table reports the 2SLS estimations of the three models used in Table 3. The instrument for inequality is agricultural endowment (*Lwheatsugar*). The numbers presented are coefficients and standard errors (in parentheses). The standard errors are clustered at country level. ***, **, * denote significance at the 1%, 5%, 10% level, respectively. T1 is the joint significance of the explanatory variables bar the two sets of year dummies (*p*-value). T2 is the joint significance of diffusion year dummies (*p*-value). T3 is the joint significance of calendar year dummies (*p*-value) and T4 is the joint significance of year-of-measurement dummies (*p*-value).

These hypotheses suggest that using the income shares of both the highest and lowest earning deciles as a measure of inequality might be fruitful. There are two problems that make it difficult to tell the two hypotheses apart using data on the income shares of both the highest and lowest earning deciles. First, the two measures are (very) strongly negatively correlated. To provide an example, the correlation between (logs of) $Incshare80100_{it}$ and $Incshare20_{it}$ is as low as −0.97. Estimating the separate effects of these two variables is therefore difficult. Second, if endogeneity is suspected, an instrument for the income share of the lowest earning deciles is needed. The instrument should show variation that is (sufficiently) independent of that of the agricultural endowment, $Lwheatsugar_i$. Otherwise, it will not allow us to identify the potentially separate causal effects of the low and high ends of the income distribution on the diffusion of mobile phones.

Table 5. *OLS and IV estimation results*

Variable	$Incshare80100_{it}$	$Incshare100_{it}$	$Incshare90100_{it}$
Panel A: OLS estimation results			
Inequality_high	14.854*** (4.193)	6.816*** (2.205)	2.120 (1.490)
Inequality_low	2.522** (1.150)	1.633 (1.070)	0.018 (1.073)
Controls	Yes	Yes	Yes
Calendar year dummies	Yes	Yes	Yes
Diffusion year dummies	Yes	Yes	Yes
Measurement year dummies	Yes	Yes	Yes
N_{obs}	289	289	289
R^2	0.856	0.854	0.847
Joint sign. of ineq. variables (p-value)	0.000	0.000	0.019
Panel B: IV estimation results			
Inequality_high	32.464* (17.849)	16.196 (10.654)	10.454 (9.055)
Inequality_low	3.138 (8.413)	0.832 (8.662)	−2.596 (9.183)
Controls	Yes	Yes	Yes
Calendar year dummies	Yes	Yes	Yes
Diffusion year dummies	Yes	Yes	Yes
Measurement year dummies	Yes	Yes	Yes
N_{obs}	289	289	289
Joint sign. of ineq. variables (p-value)	0.007	0.016	0.113

Notes: This table reports the OLS estimations (Panel A) and 2SLS estimations (Panel B) of the three models used in Table 4, augmented with the income share of the lowest two deciles (Inequality_low). Inequality_high refers to the measure used for the upper end of the income distribution (as given in the column headings). The instruments for the inequality measures are agricultural endowment (*Lwheatsugar*), a dummy that takes on the value one if the country's mean absolute latitude is less than 23.5°, and zero otherwise (*Latdum*), a dummy that identifies countries that produce and export mostly goods that are controlled by a privileged majority (*Pointsource*). We present coefficients and standard errors (in parentheses), but only for the inequality measures, which are the main variables of interest. Standard errors are clustered at country level. ***, **, * denote significance at the 1%, 5%, 10% level, respectively.

Table 5 presents the results of the OLS estimations (Panel A) and 2SLS estimations (Panel B) of equation (1), using the various measures of the income share of the highest earning deciles together with $Incshare20_{it}$ as measures of inequality. The control variables are the same as those used in Table 4. The instruments in the IV estimations are $Lwheatsugar_i$, $Pointsource_i$, and $Latdum_i$. The p-values of the tests of joint significance of the inequality measures are also reported for each specification.

The OLS results show that the income share of both the highest and lowest earnings deciles obtain a positive coefficient. Because the two inequality measures are strongly negatively correlated, we focus on their joint significance: The two measures are jointly significant at the 5 percent level in each specification. The IV results echo the OLS results, with two exceptions. First, while the inequality measures are jointly significant in the first two columns at better than the 5 percent level, the computed p-value is only 0.113 in the third column. Second, the IV estimates of the coefficients of the highest earnings deciles are clearly greater than the corresponding OLS estimates. The coefficients of the lowest earning deciles are positive in the first two columns, but negative (although insignificant) in the third.

We consider the robustness of these results below, where it is shown that the income share of the highest earning deciles is directly related to the diffusion of mobile phones, even if all the instruments are considered weak.

Discussion. Taken together, the estimation results clearly support the view that the early demand for mobile phones increases with increasing mass in the upper tail of the income distribution.

A strong potential explanation for the difference between the OLS and IV estimates in the effect of the income share of the highest earning deciles is the measurement error. If, for example, the classical measurement error is present, attenuation bias pushes the OLS estimates towards zero. However, it is also possible that there is unobserved heterogeneity across countries, leading to an omitted variables bias. Perhaps the most obvious source of such heterogeneity is the preference of the rich to use mobile phones for consumption. It is tempting to argue that this preference is positively correlated with the income share of the highest earning deciles and with high penetration rates. However, the bias observed in our results is not easily reconciled with this view, because the coefficient of the income share of the highest earning deciles increases when it is instrumented. Another plausible source of unobserved heterogeneity is the quality of the telecommunications infrastructure, if it is suspected that the control variables are not able fully to capture its cross-country variation. However, the literature on income inequality suggests that bad (political, social, and economic) institutions are associated with high inequality. If this means that (unobserved) poor quality of the telecommunications infrastructure correlates positively with the income share of the highest earning deciles, the OLS estimates would be biased upwards. The observed difference between the OLS and IV estimates is, however, not consistent with this view.

The evidence for the effects of the lower end of the income distribution on the early diffusion of mobile phones is more mixed. Our analysis provides weak evidence that if the mass at the lower end of the income distribution increases, diffusion becomes faster. This finding is consistent with the view that mobile phones are also a useful production technology for the poor, if one is prepared to maintain the assumption that a representative consumer in the developing countries could not afford to use a mobile phone (mainly) for consumption purposes during our sample period.[9]

[9] There is, however, an interesting twist to these interpretations because of the empirical measures of inequality that are available to us. On the one hand, if the rich become richer,

Robustness Analysis

Robustness to Weak Instruments. Instruments are weak (i.e., not relevant), if their incremental ability to explain variation in the endogenous explanatory variable(s) is limited. Because there is a need to use heteroskedastic-robust standard errors that allow for within-country clustering in our analysis, it is not clear how inference about the potential weakness of the instruments should be implemented. The standard approaches (e.g., the rules-of-thumb for the first-stage F-tests or the newer minimum eigenvalue tests of Stock and Yogo, 2005) do not apply, because they presume homoskedastic errors. The partial R^2 of Shea (1997), which is an alternative way to detect weak instruments, varies from 0.03 to 0.07 in the IV estimations of Table 4, and from 0.13 to 0.19 for the income share of the highest earning deciles and from 0.06 to 0.07 for the income share of the lowest earning deciles in the IV estimations of Table 5. These numbers may be indicative of the problem of weak instruments. However, evidence for or against the weakness of instruments is rarely fully conclusive.

If the instruments are weak, standard inference based on the asymptotic properties of the conventional 2SLS estimator becomes very unreliable (even if the sample size is large; see, for example, Andrews and Stock, 2005, and references therein). We address this challenge and the potential weakness of our instruments in two ways. First, we reproduce the IV results of Tables 4 and 5 using a limited information maximum likelihood (LIML) estimator. We do so because Stock and Yogo (2005) demonstrate that the LIML is potentially more robust to weak instruments than the 2SLS. Second, we use methods of inference that explicitly allow for weak instruments. To this end, we follow Chernozhukov and Hansen (2008) and invert an Anderson–Rubin-type Wald test, $W_S(b)$, which is robust to weak instruments (and which allows for heteroskedastic- and cluster-robust inference) to generate confidence intervals (sets; CIs) for the coefficients of the inequality measures.[10] It should be emphasized that the confidence

their consumption demand for mobile phones might increase even if their proportion of the population remains unchanged. In this case, income inequality (as measured by the income share of the highest earning deciles) and the diffusion of mobile phones would still be directly related. On the other hand, if the poor become richer (and their proportion of the population remains unchanged), they can more easily afford to buy a mobile phone. This possibility suggests that income inequality (as measured by the income share of the lowest earning deciles) and the diffusion of mobile phones might be inversely related. This means that we measure the mass in the tails of the income distribution in a manner that is not fully consistent with the theoretical arguments that we have put forward. However, as shown in the next subsection, our results are robust to using a measure that is based on the Gini coefficient as well as to using IV methods.

[10] Under certain regularity conditions, the Wald test, $W_S(b)$, is asymptotically equivalent to the S-statistic of Stock and Wright (2000).

Table 6. *LIML estimation results*

Variable	$Incshare80100_{it}$	$Incshare100_{it}$	$Incshare90100_{it}$
Panel A: LIML estimation results (Table 4)			
Inequality_high	25.394** (11.026)	14.658** (5.939)	14.770 (9.410)
Controls	Yes	Yes	Yes
Calendar year dummies	Yes	Yes	Yes
Diffusion year dummies	Yes	Yes	Yes
Measurement year dummies	Yes	Yes	Yes
N_{obs}	289	289	289
Panel B: LIML estimation results (Table 5)			
Inequality_high	32.135* (18.921)	16.084 (11.055)	10.448 (9.426)
Inequality_low	2.873 (9.095)	0.642 (9.108)	−2.891 (9.750)
Controls	Yes	Yes	Yes
Calendar year dummies	Yes	Yes	Yes
Diffusion year dummies	Yes	Yes	Yes
Measurement year dummies	Yes	Yes	Yes
N_{obs}	289	289	289
Joint sign. of ineq. variables (p-value)	0.009	0.019	0.127

Notes: This table reports the LIML estimations, with the estimated models corresponding to the 2SLS estimations of Tables 4 and 5. Panel A corresponds to the models used in Table 4 and Panel B to those used in Table 5. We present coefficients and standard errors (in parentheses), but only for the inequality measures, which are the main variables of interest. Standard errors are clustered at country level. ***, **, * denote significance at the 1%, 5%, 10% level, respectively.

sets that are robust to weak instruments may be empty or unbounded with a non-zero probability.

Table 6 presents the LIML results, with Panels A and B corresponding to the 2SLS estimations of Tables 4 and 5, respectively. For brevity, we only present the coefficients of the inequality measures and the associated (joint) tests of significance. The point estimates are very close to those obtained using 2SLS.

We estimate CIs or, in the case of two endogenous explanatory variables, confidence sets for two diffusion models. First, we compute the 95 percent CI for the coefficient of $Incshare80100_{it}$ using a specification that corresponds to that reported in column 1 of Panel A of Table 6 and using $Lwheatsugar_i$ as the instrument. For this model, the standard asymptotic (2SLS) 95 percent CI is $(3.8, 47.0)$. The corresponding weak-instrument CI is wider, $(7.8, 100.0)$. This interval does not, however, include zero. This implies that if the income share of the highest earning deciles increases, the diffusion of mobile phones will be faster. Second, we compute a confidence set for $Incshare80100_{it}$ and $Incshare20_{it}$ using a specification that corresponds to that reported in column 1 of Panel B of Table 6 and using $Lwheatsugar_i$, $Pointsource_i$, and $Latdum_i$ as the instruments. This confidence set is displayed in Figure 1 for the (theoretically interesting) positive orthant. The dark area corresponds to the estimated confidence set.

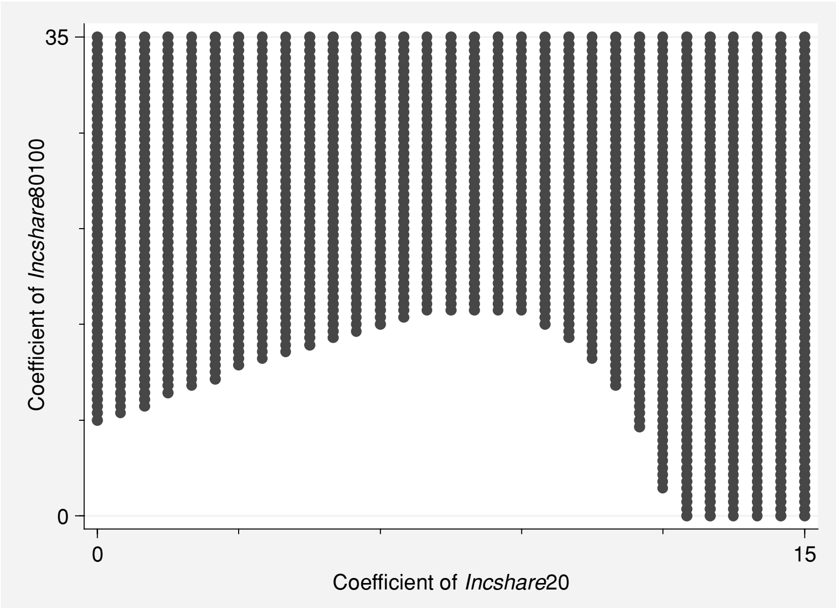

Fig. 1. Confidence set
Notes: This figure displays the confidence set for the income share of the top four deciles and the two lowest deciles, using a specification that corresponds to that reported in column 1 of Panel B of Table 6. The confidence set is robust to weak instruments and has been obtained by the procedure described in Chernozhukov and Hansen (2008). The dark area corresponds to the estimated confidence set.

Because the set does not contain the origin, we can reject the hypothesis that the coefficients of $Incshare80100_{it}$ and $Incshare20_{it}$ are simultaneously zero. The estimated confidence set shows also that we can reject the null hypothesis that $Incshare80100_{it}$ does not have an effect on the diffusion of mobile phones for all but very (implausibly?) large coefficients of $Incshare20_{it}$.

Taken together, the above robustness analysis shows that the IV results are qualitatively robust to the problem of weak instruments. The results show, as before, that if the mass in the upper tail of the income distribution increases, the diffusion of mobile phones speeds up.

Robustness to Exclusion Restrictions. Our main IV result is that if the mass in the upper tail of the income distribution increases, the penetration of mobile phones increases. The relation between the lowest earning deciles and the penetration rate is also positive, but the evidence for it is somewhat more mixed. The IV exclusion restriction on which these results rely says that the instruments are exogenous if, conditional on the included control variables, they do not affect the diffusion of mobile phones other than via their effect on inequality. As Conley *et al.* (2011) emphasize, this assumption corresponds to a rather strong ("dogmatic") prior view of how the instruments are related to the outcome of interest.

To examine whether our IV results are sensitive to relaxing the exclusion restrictions that our analysis has imposed so far, we first compute Hansen's J-tests in order to test the exogeneity of the instruments. Using $Lwheatsugar_i$, $Pointsource_i$, and $Latdum_i$ as the instruments, the J-statistic obtains a value of 0.20 (p-value = 0.90) in the model in which $Incshare80100_{it}$ is the only instrumented explanatory variable. The corresponding value of the statistic is 0.07 (p-value = 0.79) in the model in which $Incshare80100_{it}$ and $Incshare20_{it}$ are instrumented. While this evidence is not conclusive, these findings do not allow us to reject the null hypothesis of exogenous instruments.

As a second test for the exclusion restrictions, we implement (some of) the sensitivity analyses suggested by Conley *et al.* (2011). For these analyses, we do not assume that the exclusion restrictions hold exactly. Instead, we allow the coefficients of the instruments, denoted γ, be close to (but not exactly) zero in the structural ("second stage") equation. This can be done by allowing γ to have random (but local) deviations from zero, with a known (prior) distribution (see Conley *et al.*, 2011, on their "local-to-zero" method). We consider first the model in which $Incshare80100_{it}$ is the only potentially endogenous explanatory variable and in which $Lwheatsugar_i$ is the instrument. If γ has a prior distribution $N(0, 0.5^2)$, the estimated coefficient of $Incshare80100_{it}$ is 25.4, with a 95 percent CI of $[2.0, 48.8]$. For the model in which $Incshare80100_{it}$ and $Incshare20_{it}$ are the potentially endogenous explanatory variables and in which $Lwheatsugar_i$, $Pointsource_i$, and $Latdum_i$ are the instruments, we assume that γ has a prior distribution $N(0, V)$ with $V = Diag(0.5^2)$. The estimated coefficients of $Incshare80100_{it}$ and $Incshare20_{it}$ are 32.5 and 3.1, respectively. A Wald test of the joint significance of the two variables obtains a p-value of 0.057, indicating that the null hypothesis that the two variables have no joint effect on the penetration rate can be rejected (at the 6 percent significance level).

To summarize, our main IV results do not seem to be driven by implausible exclusion restrictions. The results are robust to locally relaxing the assumption of the exogeneity of the instruments.

Other Robustness Checks. We have run a number of additional robustness tests. For brevity, we do not report all of them in detail. We have, for example, re-estimated the specifications presented in Table 2 using the Gini coefficient in place of $Incshare80100_{it}$. The coefficients of the Gini variable vary from 1.9 to 2.8 and they are always significant at better than the 5 percent level. We have also estimated model (1) using the least absolute deviation (LAD) estimator. The great advantage of the LAD is that it is robust to outliers. The results are close to those obtained using OLS. For example, if we use the same control variables as those used for column 3 of Table 2, the LAD coefficients of $Incshare80100_{it}$, $Incshare100_{it}$, and $Incshare90100_{it}$ are 4.7, 2.9, and 1.7, respectively. The first two are significant at the 1 percent level and the third at the 10 percent level.

V. Conclusions

We have studied the effect of income inequality on technology diffusion using a sample of developing countries and a period covering the early stages of the diffusion process. Our results show that the effect of income inequality on the diffusion of mobile phones is positive. In particular, the mass in the upper tail of the income distribution (as proxied by the income share of the highest earning deciles) is directly related to the penetration rate of mobile phones. This finding is consistent with the view that the early phases of diffusion reflect consumption demand by the rich. The evidence for the effect of the lower end of the income distribution on the diffusion is more mixed. Our analysis provides some evidence that when there is more mass in the lower end of the income distribution, diffusion becomes faster. Assuming that a representative consumer of developing countries could not afford to use a mobile phone (mainly) for consumption purposes during the early phases of the diffusion process (i.e., prior to the end of the 1990s), this finding is consistent with the view that mobile phones have also been a useful production technology for the poor.

The findings of this paper also bear on the ongoing debate about the effect of within-country inequality on long-term development and economic growth. The three main channels that the previous literature has identified to generate a link from inequality to long-term growth are the ability of the poor to vote for redistributive policies (as opposed to growth-supporting policies; see, for example, Alesina and Rodrik, 1994), the inability of the poor to accumulate human capital when capital markets are imperfect (Galor and Zeira, 1993), and the instability and low quality of institutions that can result from the contest between the poor and the rich over political power (e.g., Alesina *et al.*, 1996; Perotti, 1996). Combined with the extensive growth literature that has confirmed the role of new technology as a determinant of productivity growth, our findings suggest that the early diffusion of new technologies may generate yet another channel that links inequality and growth.

An important limitation to this conclusion and of our analysis is that we focus only on the very early stages of diffusion and that, in our data, the mean penetration rate of mobile phones is low even at the end of the sample period. The hypothesis that we have put forward in this paper is that economies with more weight in the upper and/or lower tails of the income distribution will have higher penetration rates initially. As explained in the introduction, such a direct relation cannot be expected to hold over the whole support of the income distribution. Holding other things constant, an economy with a more even distribution of income will have a higher penetration rate for some latter portion of the diffusion path.

This type of inherent non-linearity in the relation between within-country inequality and entire diffusion path is in our view an interesting topic for further research. Whether and how within-country income inequality affects technology diffusion over the whole support of the income distribution and what the (potential) non-linear relation ultimately implies for technology-driven development and growth clearly warrants further analysis.

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First version submitted May 2008;
final version received February 2010.