The Potential of Digital Credit to Bank the Poor

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Many households in developing countries lack access to credit, and as a result let economic opportunities slip by. Policymakers have attempted to expand credit physically, by either duplicating institutions available in rich countries (bank branches and credit bureaus), or by developing new ones (microcredit). But physical interaction is costly for small loans and remote populations. Current approaches have left many excluded: two billion people around the world still lack bank accounts, according to the World Bank. But recent innovations have made possible a potentially transformative new model: digital credit delivered directly via mobile phones.

I. Digital Credit

Digital credit has become possible because of three recent innovations.

Mobile phones, first adopted for person to person communication, also represent a platform that can connect developing country consumers with digital services.

Mobile money builds on this platform, dramatically reducing the cost of transferring money (Jack & Suri, 2014). The first implementation launched in 2007 in Kenya, and there are now there are over 500m mobile money accounts worldwide (GSMA, 2016). Mobile money can be used for savings, by keeping money in the account rather than cashing it out. But it can also be used to provide credit: simply electronically transfer the loan amount, and ask that the recipient repay later. Of course, the recipient may not repay. That problem—how to increase the likelihood of repayment in a low information setting—is addressed by the third innovation.

Few of the world's poor interact with institutions that generate the data needed for traditional credit scoring—many only rarely transact with formal systems at all. However, this is changing: the use of a mobile phone itself generates digital traces of behavior. These include not only mobile money usage, which tends to be sparse, but also patterns of calls, top up, and mobility. These traces represent the richest behavioral data available on many of the world's poor. Björkegren

(2010) suggested that these behaviors may predict repayment, and proposed using them to generate alternative credit scores. Björkegren and Grissen (2015, 2017) find that risk scores developed with this method are predictive, and can reduce the risk of providing a loan.[1] After individuals have obtained an initial digital loan, they start to build a credit history which can complement initial scoring, and incentivize repayment (Carlson, 2017).

This combination of technologies has spurred what appears to be an emerging revolution in lending (Francis, Blumenstock, & Robinson, 2017). The first service lending over mobile money launched in Kenya in 2012 (M-Shwari), and over the following years, a flood of products has followed. Already in Kenya, more individuals have loans through these new digital platforms than through traditional banking or microfinance (FSD, 2016).

However, so far, many of these loans are small, short term loans made to urban smartphone users, rather than investment loans made to the rural poor. Is the current menu of products a result of technological constraints, or can digital financial services transform finance for the poor?

The first barrier to inclusion in digital credit is being scored. Poor consumers tend to leave sparser digital footprints, because transactions cost money and battery life. This paper sheds light on what groups might be technologically included and excluded from digital credit.

II. How Technology Can Expand Credit

Consider a stylized model of a lender that is deciding whether to provide a loan to an individual. The individual may be one of two types: a repaying type will result in gain G, or a defaulting type will result in loss L. For simplicity, assume either type is equally likely. The lender does not know which type the individual is, but has a screening technology that provides a noisy signal, s, that corresponds with the true type with probability $\gamma \geq \frac{1}{2}$, or the opposite otherwise. If the lender provides a loan only when it believes the individual will repay, it will receive expected profits:

$$E\pi = \frac{1}{2}[\gamma G - (1-\gamma)L - F] \quad (1)$$

where F is the overhead cost of dispersing a loan (including screening costs). The lender will provide a loan if:

$$\frac{L}{G+L} \leq \gamma - \frac{F}{G+L} \quad (2)$$

Providing credit digitally can lower marginal overheads, F, to near zero. That can make

[1] Other alternative measures can also be used for credit scoring, such as psychometrics (Klinger, Khwaja, & LaMonte, 2013).

feasible new forms of loans, and loans to previously excluded populations. Which loans are feasible to provide will be determined by the lending risk—described by gain relative to loss (G and L), and the ability to screen, γ.

III. The Scope for Scoring the Unbanked

To test the ability of digital credit to reach the poor, we expand on Björkegren and Grissen (2017). We focus on a middle income Latin American country where only 34% of adults have bank accounts but 89% of households have mobile phones. We partnered with a telecom that was transitioning prepaid subscribers to postpaid plans, which entails an expansion of credit. We worked with the telecom to predict who would repay, in a retrospective analysis.

Our setting has two crucial features. First, in the introductory period we study, the telecom approved borrowers using only minimal fraud checks, so we observe outcomes among the full sample of individuals to whom it would conceivably consider providing credit. This allows us to evaluate the performance of any scoring rule. Second, the sample includes a mix of unbanked and banked consumers. For consumers with formal financial histories, we benchmark performance against that of models using credit bureau data.

We use the same setup as Björkegren and Grissen (2017), with an anonymized sample of 7,068 individuals who received credit. We generate 5,541 measures of behavior from mobile phone usage, prior to receiving credit. These behaviors were linked to an indicator of whether the credit was repaid, and any credit bureau records. We then use machine learning to create predictive models. Following standard practice in credit scoring, we measure the predictive performance of the model with the Area Under the ROC Curve (AUC), an analogue of γ, which ranges from 0.5 to perfect power at 1.0. We use random forests for both our base model (CDR) and a more conservative model that attempts to avoid intertemporal overfitting (CDR-W). Because random forests performed poorly with bureau data, we use the better performing logistic stepwise regression for bureau models.

This article evaluates the ability of these models to score different groups of traditionally excluded individuals. We assess performance with 5 fold cross validation. The model is trained on all individuals except the omitted fold, and performance is reported for the given subsample (e.g., women) within the omitted fold.

By subgroup.— Figure 1 evaluates performance by subgroup (the top panel, for individuals with bank accounts, and the bottom without). The top lines in each panel report results from Björkegren and Grissen (2017). In our sample of thin file consumers, credit bureau models do not perform well. CDR models perform slightly better than credit bureau models, but also work for those without bureau files. Although our error bars can be wide, performance is not widely heterogeneous across groups, suggesting the method may be able to score different types of individuals.

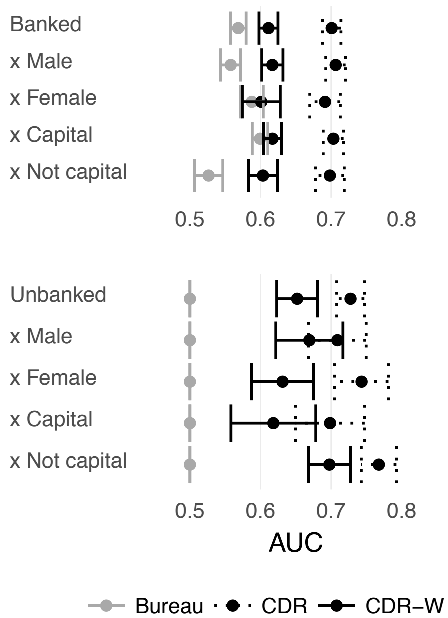

FIGURE 1. PERFORMANCE BY SUBSET

Note: Bars represent 1 standard deviation.

By usage.— We also assess the performance on individuals with records of varying sparsity, in Figure 2. Nationwide, households with bank accounts tend to spend more on mobile telephony than those without, as shown in the top panel. Our sample of prepaid users is drawn from the higher end of the national distribution.

The middle panel breaks down performance by quartile of usage in sample. Performance within each quartile is similar to overall performance, which suggests the method picks up nuances in usage, not simply overall usage.

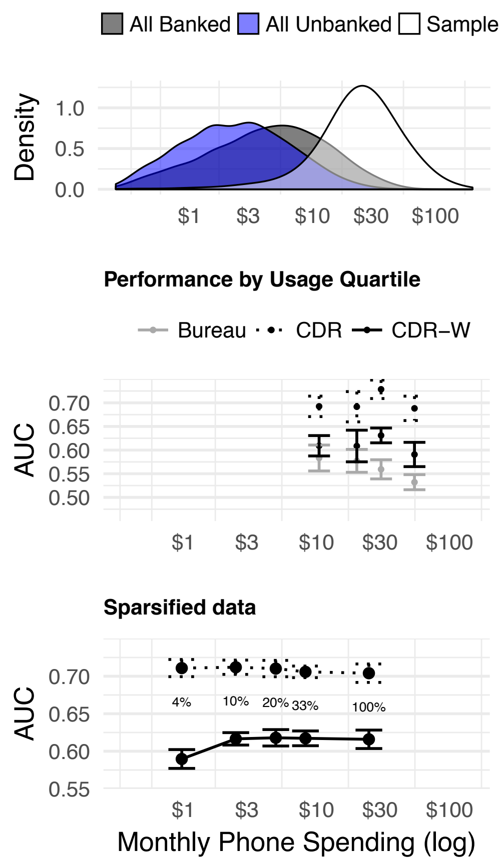

FIGURE 2. PERFORMANCE BY PHONE USAGE

Note: Sparse CDR models derived from subsampling every *k*th transaction transactions. Bars represent 1 standard deviation. In our sample, spending is measured per phone account. National spending levels obtained from a household survey; that survey reports total spending per household. To be conservative, we divide report phone spending per adult; if not every adult has a mobile phone this will overstate the difference with our sample.

We also assess performance when usage is sparser, by creating synthetic datasets that includes only a fraction of the original transactions, which span the lower range of usage of unbanked households in the country.

We observe some deterioration in this lower range with CDR-W, as shown in the bottom panel. We expect performance to improve when observing individuals for longer time periods, or as usage of technology increases.

IV. Discussion

The digitization of developing economies has greatly expanded the space of feasible designs for consumer financial products. This article explores one dimension of this flexibility: the potential to generate risk scores for different types of consumers. But there is much more flexibility to explore. Digitization also reduces the overhead for small transactions, makes it easier to create products with ongoing and dynamic interaction, and provides new sources of data on which insurance payments can be conditioned. Although private firms are exploring this design space, the products that deliver the highest private returns may not coincide with those that deliver the highest social returns. If so, the public and social sectors may need to engage with product development to reach the full potential of this apparent financial revolution.

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