

# Public policy and the promise of digital credit for financial inclusion

C. Leigh Anderson<sup>\*a</sup>, Pierre E. Biscaye<sup>a</sup>, Adam L. Hayes<sup>a</sup>, Marieka M. Klawitter<sup>a</sup>, and Travis W. Reynolds<sup>b</sup>

<sup>a</sup> Daniel J. Evans School of Public Policy and Governance, University of Washington

<sup>b</sup> Environmental Studies Program, Colby College

Corresponding author email: cla@uw.edu

## Abstract

Digital credit products are characterized by a lending process that is instantaneous, automated, and remote. While digital credit has the potential to reach less collateralized, less mobile, and more remote cohorts of borrowers, there are also risks in relying on digital credit for financial inclusion. This paper investigates the digital credit policy environment and the extent to which it may support pro-poor digital credit market development using two types of documents: a set of 23 regulatory documents specifically mentioning either digital or online credit or lending, and another set of 298 informal documents relevant to digital credit based on a systematic web search. After reviewing the literature on the effects of credit expansion and automated credit scoring, we summarize the characteristics of the current digital credit regulatory environment in low- and middle-income countries. Our findings suggest that few regulations specifically target digital credit markets, and that the current regulatory environment may not support the full potential of digital credit to reach historically underserved credit consumers. Most countries do not explicitly target financial inclusion as part of their digital credit policies. However, we do find evidence that informal web documents consider financial inclusion to a greater extent than formal regulatory documents.

**Keywords** – Digital credit; Regulation; Financial inclusion; Consumer protection

## 1 Introduction

Digital credit products refer to loans that are “instant” (take no more than 72 hours for approval and disbursement), “automated” (use alternative credit data and algorithms to score potential borrowers), and “remote” (accessible with minimal physical human interaction). Developed as a result of increasingly widespread access to mobile services in developing countries and increasing availability of

alternative data for credit scoring, digital credit products may offer loans to customers who have historically lacked access to the formal financial system, including those lacking documentation, credit history, a bank account, or physical proximity to financial services. Hence the potential for digital credit to reach the less collateralized, less mobile, and more remote could be significant (Parada & Bull, 2014; Costa et al., 2016).

As digital lending activities become more common, we ask: to what extent do existing or proposed digital credit regulations consider particular cohorts of previously underbanked and potentially vulnerable borrowers? As background we turn to the existing literature to understand how the expansion of digital credit might impact particular cohorts of borrowers that are underserved in traditional credit markets, and how those cohorts can be defined. This background provides guidance for our subsequent search to understand how existing or emerging policies and regulations governing digital credit providers and markets support the technological capability of reaching previously unbanked individuals – the promise of digital credit.

### 1.1 Digital credit and financial inclusion

Only 62 percent of adults worldwide are estimated to have an account at a formal financial institution, leaving over 2 billion adults unbanked, the vast majority in Asia, Africa, Latin America and the Middle East (Chaia et al., 2009; Demirgüç-Kunt et al., 2015). Of those unserved by conventional banking, more than half are in the poorest 40 percent of households in developing countries. The gender gap persists at about 11% (58 percent of women with a bank account versus 65 percent of men) though the gap is higher in South Asia, where 37 percent of women have an account compared to 55 percent of men (Demirgüç-Kunt et al., 2015). Overall unbanked individuals tend to have above average illiteracy rates, with women further constituting 2/3 of the illiterate adult population; income flows are also often low and unpredictable or seasonally variable, compromising payback (Grossman, 2017).

In this environment digital credit has the promise of reaching large populations of previously under-served individuals seeking credit. However a recent assessment by CGAP suggests that for the previously unbanked distinct consumer protection risks of digital credit include: “low-income consumers’ poor understanding of loan costs and the consequences of default, which can be exacerbated by interface limitations, such as small screens and short menus; their lack of ‘intentionality’ when making borrowing decisions on the spot; and the opportunity to easily renew a series of high-cost loans” (Mazer & McKee, 2017, p.1).

The “promise” of digital credit thus rests on whether the technological ability to have a broader reach is also financially attractive to suppliers, and whether the newly reached borrowers, on net, benefit from that access. Policy will affect both of these outcomes, but will likely also involve tradeoffs on both sides between regulating risks and returns. For suppliers, the numbers of borrowers, lending margins, and the cost and rate of default will help determine expansion. Previously excluded consumers, by definition, will lack credit experience and often credit histories, making good access to information on both sides of the market important for encouraging a competitive market. Information becomes particularly important if the less collateralized (e.g., the poorest), less mobile (e.g., women) and more remote (e.g., rural) cohorts of borrowers are systematically different credit consumers: with a different credit demand or probability of payback.

The evidence from microfinance provides a starting point for understanding how socio-economics and demographics may affect the demand for credit (Mar et al., 2016; Steinert et al., 2017), as does the emerging literature on access to mobile phones and digital financial services (DFS) more broadly (Cummings & O’Neil, 2015; Assensoh-Kodua et al., 2016). There is a smaller literature on probabilities of default, particularly among traditionally excluded sub-populations who were not receiving loans. “Remote” households that are agriculturally based are the most vulnerable to seasonal variation and climate shocks that may affect anticipated revenue streams, as are subsistence households with small margins to absorb negative health or other shocks (Hill & Porter, 2017).

Classification of borrowers into credit risk categories has also more recently benefited from the emergence of automated digital credit algorithms that utilize alternative data to supplement or replace traditional credit histories in order to predict credit risk, including mobile (Bjorkegren & Grissen, 2015; Luvizan et al., 2015; San Pedro et al., 2015; Yu, 2017) and landline (Eagle et al., 2010) phone data, social media data (Freedman & Jin, 2017; Tan & Phan, 2016; Wei et al., 2016), and credit card data (Singh et al.,

2015). This body of literature has identified a number of behavioral or consumer variables not directly related to financial or credit history that can be useful in credit risk prediction, including: mobility patterns (San Pedro et al., 2015; Singh et al., 2015), friend connections in social networking sites (Tan & Phan, 2016; Wei et al., 2016), mobile phone call and storage patterns (Bjorkegren & Grissen, 2015; Yu, 2017) and mobile airtime purchases (Decuyper et al., 2014; San Pedro et al., 2015). Many of the researchers that investigate alternative data sources are optimistic that the use of alternative data in classification algorithms will help extend the credit market to the underbanked who have had little or no prior contact with formal lending institutions (Bjorkegren & Grissen, 2015; San Pedro et al., 2015; Tan & Phan, 2016).

However, an additional concern with digital credit is that automated credit scoring using alternative data approaches will produce a bias due to the inability of algorithms to accurately discern between dissimilar borrower cohorts (Hwang, 2016) or anticipate or adapt to changes in context (Lepri et al., 2017). Machine learning algorithms can easily perpetuate existing biases in ways that are not easily detectable (Caliskan et al., 2017). For example, because there is no objective measure of ‘credit worthiness’, the measure is typically taken from existing definitions under traditional credit systems, thereby perpetuating whatever biases may be inherent in existing measures of credit risk (Barocas & Selbst, 2016). While the purpose of credit scoring algorithms is to directly discriminate between borrowers on the basis of credit risk, automated credit algorithms may also indirectly discriminate between cohorts on the basis of characteristics that co-vary with credit risk (Lepri et al., 2017). Asymmetries in data availability may likewise produce biases in machine learning classification algorithms (Barocas & Selbst, 2016). As a result, even “unbiased” machine learning algorithms can produce asymmetries in error rates between groups that can lead to systematic disadvantages for particular groups (Chouldechova, 2017). Given the limitations of machine learning algorithms, there is some concern that the increasing use of alternative credit scoring will simply make the underbanked appear to be prohibitively risky borrowers rather than potential customers for lenders (Aitken, 2017).

## 2 Methods

Like other digital financial services, such as mobile money, digital credit exists in an overlapping regulatory environment (Arner et al., 2015; Blechman, 2016). For instance, digital credit products that use a mobile money platform to approve and disburse loans may fall under the regulatory authority of a financial regulator, a

telecommunications regulator, and a competition authority all within one country, so a broad approach to identification of policy documents is required. We compiled an original database of regulatory documents using Google and Google Scholar search engines to return results for a series of search strings related to keywords concerning digital credit policy. We screened each search result for policy relevance to digital credit, and identified regulations that may affect digital credit products in Asia, Africa, and Latin America.<sup>1</sup>

In order to gather documents relevant to the broader policy discussion around digital credit, we also conducted a separate automated Google search using a combination of general and country-specific search strings focused on digital/mobile money/credit and policy/regulation. In all, we searched 50 total strings and gathered the first 70 results from each search.<sup>2</sup> After removing duplicate pages and filtering for relevance, we were left with a corpus of 298 web documents. These documents are not specifically regulatory - instead, they include blogs and news items, industry websites, NGO websites, etc. as well as government web documents. Because these web documents do not necessarily represent regulatory documents, we keep them separate from the database of regulatory documents and treat them separately in our analysis. We attributed these documents to countries according to the proportional number of occurrences of a country name in the document, allowing for partial attributions.

Table 1. Keyword lists for online searches

Cohort	Key Words (terms were stemmed and variants were included in the search)
Female	Female, Woman, Girl, Wife, Mother, Daughter
Rural	Rural, Farm, Agrarian, Agriculture, Peasant, Subsistence
Poor	Poor, Poverty, Impoverished, Underprivileged, Beggar, Peasant, Slum, Subsistence
Non-specific	Less/Least privileged, Underbanked, Under-represented

Given the promise of digital credit products to bring greater inclusivity to credit markets, we investigated whether the documents we identified - both regulatory and more general documents - include particular considerations for borrowers that have been underrepresented in traditional credit markets. We undertook a text string search across both sets of documents separately for any words related to female borrowers (less mobile), borrowers from rural areas (more remote), or poor borrowers (less collateralized), in order to calculate whether and how frequently each document uses words related to these under-served cohorts (Table 1).

<sup>1</sup> See Anderson et al. (2017) for additional methodological details

### 3 Findings

#### 3.1 Digital credit policy environment

Our research question asks what current policies specifically target the digital credit market and whether these policies take particular borrowers into account. Remarkably, none of the regulatory documents we identified include the term ‘digital credit’. Instead, we identify documents that fall at the intersection of two regulatory frameworks: (a) the laws and regulations that apply to ‘credit’ and finance more broadly; and (b) the laws and regulations that govern digital transactions. In all, we identified 23 policy documents across 15 countries (plus Hong Kong) in Africa and Asia with regulations that specifically mention digital or online credit or lending. We were unable to find relevant regulations for any Latin American country.

To summarize the policy environment more generally, we divide regulatory issues surrounding digital credit into two broad categories (Table 2). *Market conduct* policies include five policy subcategories related to the competitive conduct of providers in the market and to protecting the consumer from unfair practices: data management and privacy, product disclosure, consumer redress, consumer over-indebtedness, and rates or pricing. *Systemic risk* policies also include five subcategories related to the stability and maturity of the credit market: licensing and reporting requirements, lending prohibition, regulatory sandboxes, capital requirements, and governance requirements.

Figure 1. Coverage of digital credit regulatory dimensions (max=5/category)



As summarized in Figure 1, no country has addressed all of the regulatory issues we identified through this review. And even the countries with the greatest regulatory coverage

<sup>2</sup> These searches were for web documents related to digital credit policy more broadly - the string searches did not specifically target any of the keyword terms in Table 1.

Table 2. Regulatory issues that affect digital credit in selected Asian and African countries and jurisdictions

Regulatory Issue		Brief Description of Regulatory Approach	Number of Regulations	Countries/Jurisdictions with Regulations
Market Conduct	Data Management and Privacy	Data privacy, Data management requirements, Confidentiality	10	Bangladesh; China; Ghana; India; Indonesia; Pakistan; Zambia
	Product Disclosure	Transparency of fees, charges, terms, etc.	6	China; India; Kenya; Tanzania; Zambia
	Customer Redress	Redress procedure, Complaint center	4	China; India; Ghana; Pakistan
	Consumer Over-indebtedness	Lending amount limits	2	China; Indonesia
	Rates and Pricing	Rate caps, Length of loan terms, Competitive pricing	1	Kenya
Systemic Risk	Licensing and Reporting Requirements	License requirements, Business continuity plan, Reporting requirement	7	Bangladesh; China; Ghana; India; Indonesia; Pakistan; Zambia
	Lending Prohibition	Prohibits lending from certain types of institutions	6	Democratic Republic of Congo; Ghana; Lesotho; Malaysia; Sri Lanka; Zambia
	Regulatory Sandboxes	Allow organizations to experiment with new financial technology models with minimum supervision within defined time and space limits	5	Hong Kong; Indonesia; Malaysia; Singapore; Thailand
	Capital Requirements	Equity in relation to debt, Ratio of capital to risk-weighted assets	5	India; Indonesia; Ghana; Pakistan; Zambia
	Governance Requirements	Managing financial risk, Managing maturities of loans and investments, Organizational governance standards	2	India; Indonesia

Source: Anderson et al. (2017)

(i.e., Indonesia, India, and China) have regulatory gaps that are potentially threatening the viability of digital credit as well as the potential for financial inclusion. Many of these regulations, particularly along the market conduct dimension, have particular relevance for historically under-served borrowers. Borrowers with less credit market experience, for example, may over-borrow, they may also be subject to less favorable rates, and be more vulnerable to data privacy issues given the reliance on alternative ‘big data’ sources to evaluate their credit risk.

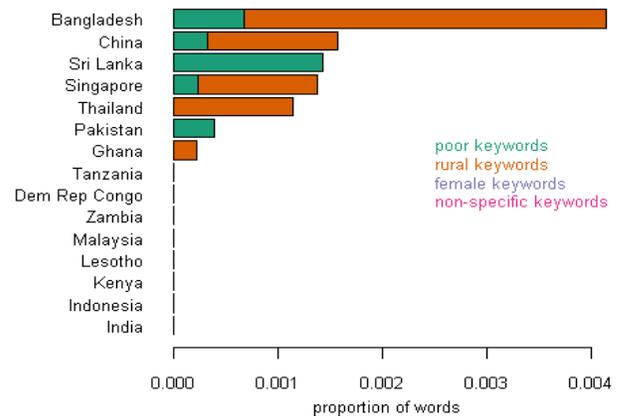
### 3.2 Inclusivity in regulatory documents

Given the promise of digital credit products to bring greater inclusivity to credit markets, we investigate whether the identified regulatory documents include particular considerations for borrowers that have been underrepresented in conventional credit markets. Borrowers who are less collateralized, less mobile, and more remote may have less difficulty accessing the digital credit market compared to bank-based credit markets.

Looking for relevant keywords across 23 regulatory documents reveals a general lack of consideration for borrowers who may disproportionately use or benefit from digital credit compared to more traditional credit markets. Only 7 documents contain at least one mention of keywords associated with poverty, and only 6 mention a keyword associated with rural borrowers. None of the regulatory

documents include any of the female keywords we defined (Figure 2).

Figure 2. Cohort-relevant keywords in regulatory documents by country (n=23 documents).



We consider keyword frequency as one measure of relative consideration for our three historically under-served borrower cohorts of interest. At the country level, we find that regulatory documents from Bangladesh are associated with one of our three dimensions of inclusivity to a relatively large degree (0.4% of the words used related to poor, rural, or female borrowers), far exceeding the other countries represented in our regulatory document database. By comparison, some of the most frequent words in these documents such as ‘account’ and ‘money’ make up 0.7%

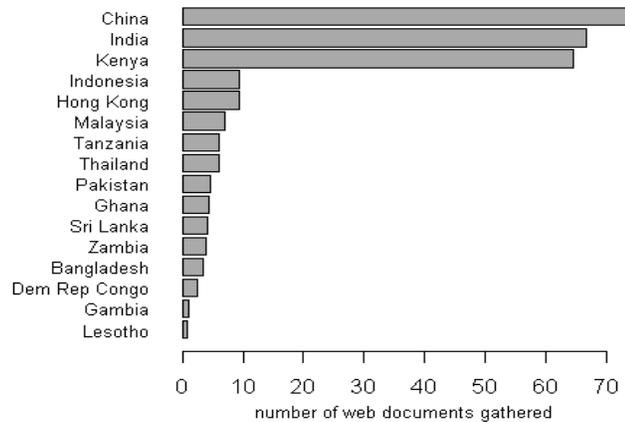
and 0.9% of words used, respectively. In all, seven of the fifteen countries represented in our regulatory database have keywords associated with either poor or rural borrowers in their regulatory documents; eight countries have none.

The presence of these keywords may signal that a country is crafting legislation to increase the inclusivity of credit markets, as is the case with Bangladesh and China - both of which have undertaken deliberate policies to encourage access to financial services for the rural and urban poor.<sup>3</sup> For example, the Bangladesh mobile financial services guidelines specifically take expansion of digital banking to the low-income segments of the market as the stated purpose for the regulations (Bangladesh MFS, 2015).

### 3.3 Inclusivity in informal documents

When we look at the more general non-regulatory web documents from our automated web search, we find first that discussion of digital credit online is dominated by three countries: India, China, and Kenya (Figure 3).

Figure 3. Number of relevant web documents gathered by country (n=298 informal documents)

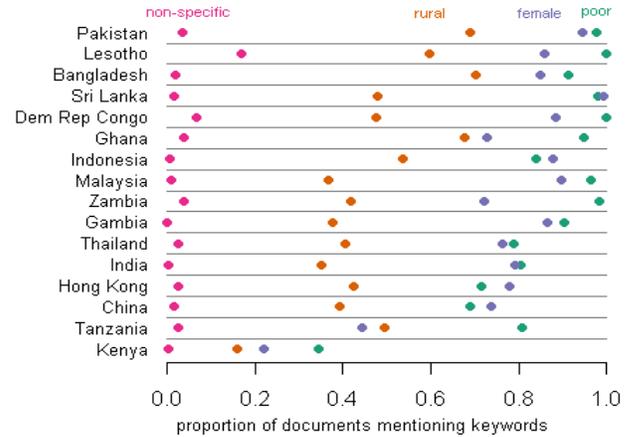


In contrast to the regulatory documents, for most countries upwards of 40% of each country's web documents in our sample mention each of our keywords of interest (Figure 4), with words that relate to poor borrowers appearing most frequently followed closely by female-related keywords. Rural keywords appear less frequently, perhaps indicating the prioritization of poor borrowers regardless of geography. This is consistent with the language of some of our regulatory documents that aggregate low income groups across rural and urban areas (e.g., Bangladesh MFS, 2015). Kenyan documents feature considerably fewer mention of our keywords than other countries, followed by Tanzania and China. These results at least initially suggest that the issue of access to digital credit for marginalized borrowers,

<sup>3</sup> We note that the presence of keywords doesn't necessarily correspond to policy focus. Sri Lankan regulations mention 'poor' in the context of sub-par services rather than low-income

female borrowers in particular, is more prevalent in the online discussion than in formal regulatory documents.

Figure 4. Proportion of each country's documents mentioning cohort-relevant keywords (n=298 informal documents). A value of 1.0 indicates that 100% of that country's non-regulatory documents included the corresponding keyword term.



## 4 Conclusions

Some authors have recently argued that policies to fulfill the promise of digital credit for traditionally unbanked individuals appear to be lagging the technological opportunities. Individuals living remotely with risky livelihoods, for example, could potentially be well served by affordable and accessible digital credit to smooth consumption, make investments, and cushion income shocks (Beaman et al., 2014). But there are practical and perceived challenges that limit adoption of digital credit and increase default rates, including illiteracy and variability or unreliability of income flows, complicated DFS menus and user interfaces, and sparsity of data with which to generate accurate and unbiased credit scores, coupled with related issues of data regulation and privacy. There are also behavioral biases, such as hyperbolic discounting, some of which are heightened through marketing choices for default settings and framing, or poor disclosure of pricing, fees, and terms and conditions (Grossman, 2017).

Some of these challenges – though certainly not all -- may be addressed through policy and regulation making digital credit products more approachable for unserved populations and promoting the design of digital credit products tailored to these populations. Our results suggest considerable online attention to these issues and the sub-populations hypothesized to be most vulnerable, as yet unmatched by

users, and regulatory documents from Ghana mention rural banks only to exclude them from the regulatory framework.

traction in formal regulatory documents. While these findings are suggestive, these results may be extended by applying natural language processing techniques to increase the accuracy of our keyword search. Documents may also be collected longitudinally over time to study how regulatory language evolves to increase financial inclusion. Further review may also consider regulatory documents that apply to digital financial services more broadly, as these may also be applied to digital credit.

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