# The Patterns of Loan Distribution under the Development Credit Authority Program

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**Abstract**

Using data provided by USAID on the Development Credit Authority (DCA) loan program, which aims to promote economic development through credit guarantees, we employed OLS Regression and Machine Learning models to estimate the determinants of loan size. The region, business size and sector, and the gender of the entrepreneur have significant effects on the final loan amount received by the borrower. Women entrepreneurs receive more than 25% smaller loans than male entrepreneurs for similar businesses and are given loans at a rate below the number of businesses they own nationally. These findings suggest the following improvements to the program: 1. Reducing the political influences on the program, 2. Better assessments on if loans are going to business owners who would not have otherwise, and most importantly, 3. Increasing loan frequency and loan amounts to women entrepreneurs.

# 1 Introduction

## 1.1 The Motivations and Effectiveness of Foreign Aid

From 2013-2018, nearly 300 billion USD were spent on foreign aid by the US government (Andrzejewski, 2021), but where and to what effect did these dollars go to? Foreign aid has long been an area of keen interest in the field of development economics given its potential to help eradicate world poverty, yet the efficacy of foreign aid is frustratingly unclear [1]. Nevertheless, the urgency of the fight against global poverty is undeniable, especially as the global extreme poverty rate (defined as living on $2.15 or less per day, 2017 PPP) rose for the first time in three decades to 9.3% in 2020 (World Bank, 2022b). Perhaps the question: "Does foreign aid work?" is flawed. Given that "[foreign] aid allocations may be very effective at promoting strategic interests, but the result is that bilateral aid has only a weak association with poverty, democracy, and good policy," it would be presumptuous to think all types of politically-motivated aid programs work (Alesina and Dollar, 2000). Thus, analyzing the delivery and results of a specific aid program, while less exciting, is likely more productive. The United States Agency for International Development (USAID) is one of the agencies responsible for delivering aid to countries. This paper analyzes the delivery of USAID's Development Credit Authority (DCA) program, and how this affects the program's results.

## 1.2 The Development Credit Authority

The DCA program backs local banks with partial credit guarantees to share the risk of lending to businesses that are typically perceived as "too risky" to finance. If the business defaults, the program would partially pay the bank back for the lost loan amount. Since the credit guarantees are partial (typically only half of the loan amount) and only need to be executed in the case of defaults, it costs relatively little to mobilize a large amount of capital. For example, in 2016, it is expected to have cost only $28 million to generate up to $891 million of loans, 32 times the cost (Tarnoff, 2017).

Unsurprisingly, these "too risky" businesses neglected by banks tend to be micro, small, and medium enterprises (MSMEs) that are new (Bawaba, 2014). The theory of change is that banks will realize lending to some MSMEs is not as risky as initially perceived and sustain it themselves after the program stops (USAID

[1] See *The End of Poverty* by Jeffery Sachs and *Dead Aid* by Dambisa Moyo for competing views on the efficacy of Foreign Aid.

Video, 2012). This program alleviates the asymmetric information problem causing inefficient loan supply. MSMEs do not have a credit history resulting in higher risks for banks, but once a positive credit history is established, banks are more willing to sustain the loans themselves without the DCA.

### 1.3 The Determinants of Loan Size in the DCA Program

While perhaps theoretically sound, what does the program deliver in reality? Does the program suffer from the typical strategic political interests, and inevitably compromise on the premise of providing credit to neglected entrepreneurs? To answer these questions, we generalized these ideas to the research question: "What are the underlying patterns of loan distribution under the Development Credit Authority program?"

We found in the data that the region, business size and sector, and gender of the entrepreneur have significant effects on the final loan amount received by the borrower. Region effects were found to be even better captured by our machine learning model using country indicators, suggesting loan sizes depend on the country. Business size and sector have expected impacts, with increasing loan sizes with the former, and high variability with the latter. The gender impacts on loan size was perhaps the most unexpected. For example, 32% of loans by the program were made to women, while only 9% of the total funds backed by the program ended up to women, largely explained by the fact women rarely receive loans larger than $5,000. Controlling for relevant features such as region, business size and sector, women are still estimated to receive over 25% smaller loans in our OLS and Machine Learning models. This suggests there are serious equity issues in the way loans are being distributed. Using these results, we identified obvious improvements to the DCA program in the facets of 1. Reducing the influences of politics, 2. Better assessment of if loans are going to business owners who would not have others, and most importantly, 3. Increasing loans and loan amounts to women entrepreneurs.

## 2 Literature Review

Overall, the literature available to the public on the DCA program is limited, with the majority of reports being by the DCA and other governmental institutions. The program especially lacks quantitative measures of the program's effectiveness and its loan patterns. Our paper addresses this gap by clearly identifying these patterns and further exploring the implications on overall program effectiveness.

From these reports, there is no shortage of anecdotal evidence portraying different success stories of the DCA program (USAID Video, 2012; Tarnoff, 2017). One particularly powerful story is in Uganda, Dr. Tumwesigye wanted to start an AIDS clinic "...but we tried to get money from various banks. We were turned down mainly because of the rural area." But under the support of the DCA program, they received a loan for $35,000 USD to purchase equipment and hire staff "to provide AIDS care for over 4,600 patients, who are now living because of that loan." Given the program's potential to do this much good, it is important to more rigorously study this program and what it has achieved from a quantitative perspective.

### 2.1 The Credit Gap in Development

It is a well-studied fact that there is a credit gap in which many MSMEs in developing nations get trapped. A business becomes too big to lend from local moneylenders (that charge excessive interest rates) and yet too small for local banks that are only willing to loan to well-established businesses (Banerjee and Duflo, 2012). In fact, according to development economists Abhijit Banerjee and Esther Duflo, "Finding ways to finance medium-scale enterprises is the next big challenge for finance in developing countries." Clearly, the theory behind the DCA is solid. The program tackles a key issue in developmental finance by reducing barriers that certain businesses face in the banking system.

### 2.2 The Effectiveness of Microfinance

Since the literature on the DCA program lacks any serious studies on its effectiveness, we turn to the related world of microfinance which has a growing body of literature on its results. Overall, the evidence for the effectiveness of microfinance is mixed and does not live up to its reputation as a silver bullet for poverty as popularized by the media (Marr, 2012; Westover, 2008). Marr points to the fact there are a "significantly limited number of rigorous studies, especially about rural microfinance ... [and] that evidence of effectiveness is mixed, suggesting that the impact effects of microfinance are inconclusive." Similarly, Westover warns "...government policymakers must exercise caution and restraint in applying the microfinance approach universally as a means of alleviating poverty." The main strength of our paper comes from directly addressing Marr's concern by using a rigorous data-driven approach to draw conclusions about the DCA program.

On the other hand, using a randomized control trial, Banerjee and Duflo found a measurable, but small positive impact of the Spandana microfinance program, increasing entrepreneurship rates from 5 to 7 percent, so microcredit is likely "*one* of the key instruments in the fight against poverty" (Banerjee and Duflo, 2012).

While both the DCA and microfinance address the same issues with access to regular financial institutions and provide an alternative to moneylenders, there are some fundamental differences between the DCA program and microfinance. The target audience of microfinance is to help individuals and households to cover personal expenses (health, housing etc.) and start micro-enterprises, while the DCA is for MSMEs (micro, small, and medium enterprises). More importantly, the DCA program is a direct partnership with banks, allowing loanees to establish a credit history with banks for future loans outside of the DCA, paving a path for long-term growth. Thus, inferences cannot be made about the effectiveness DCA program from past studies on microfinance. Furthermore, given the mixed bag of results from microfinance, it is clear that microfinance only works in certain environments, and not universally, so drawing parallels between these two distinct types of programs would still yield inconclusive results. While our paper is unable to directly address the DCA program's effectiveness, understanding the patterns of loan distribution is one of the key steps to understanding why or why not it might be effective and any room for theoretical improvements.

### 2.3 Female Entrepreneurship for Sustainable Development

In the past two decades, there has been rapid growth in the understanding of the importance of female entrepreneurship to economic development. While gender equality is a social goal in its own right, "greater gender equality is also smart economics, enhancing productivity and improving other development outcomes" (World Bank, 2012). A more recent study finds "...women participation in entrepreneurial activities not only supports... their family income but also plays a significant role in economic development and social well-being of the society" (Sajjad et al., 2020). Given the overwhelming evidence of the development value of investing in female entrepreneurship, our paper evaluates how the DCA program's lending patterns align with this evidence. Indeed, in a 2020 report by USAID, DCA's (former) parent organization, the authors admit that "women face multiple barriers to accessing financial resources and facilities. Promoting financial services to women is an important factor in improving women's access to entrepreneurship." (Jazouli et al., 2020). Our paper uses quantitative evidence to show that the DCA program does not do enough to address this key priority.

### 2.4 Conflicts of Interests in the DCA Program

In 2019, Congress approved the U.S. International Development Finance Corporation (DFC) to assume the functions of the DCA out of 'interest in elevating U.S. efforts to respond to China's "One Belt, One Road" initiative,' a Chinese foreign aid policy (Akhtar and Brown, 2022). In fact, the report admits there is "tension between DFC's development mandate and efforts to counter strategic and economic competitors." Clearly, the DCA program is not immune to the demands of political strategy as identified by Alesina and Dollar. Indeed, the DCA states that the program aims to "design and deliver investment alternatives that unlock financing for U.S. Government priorities" (USAID, 2019). Our paper finds drastic differences between average loan sizes and funding available depending on the country that cannot be reasonably explained by development priorities, giving strong evidence that the DCA is targeting other goals, which the literature indicates is likely political.

# 3 Methodology

## 3.1 Data

We obtained the publicly available data from USAID of all private loans backed by the DCA from 1999-2016. This includes over 160,000 entries on the date, size of the loan and business, geographic location, business sector, gender, and first-time borrowers (USAID, 2022, 2019). This data will allow us to identify how the quantity and sizes of loans associates with certain characteristics. Gender and first-time borrower data are only available after 2008. We also merged the following country indicators:

- GDP per Capita 2010 (World Bank, 2018)
- The Gender Inequality Index (GII): This indicator measures the overall gender inequality in reproductive health, empowerment and the labour market. (United Nations, 2023).
- Women, Business and the Law Entrepreneurship Score (Average Entrepreneurship Score): This indicator measures the legal constraints for women to start a business. We took the average of available scores from 1999-2016 (World Bank, 2023).
- Firms with female participation in ownership (% of firms) (Female Participation Rate in Ownership): This indicator measures the percentage of firms in a country with a woman that is one of the principal owners (World Bank, 2022a).

GDP per Capita will be useful to proxy development needs, and the latter three will be used to evaluate how the DCA promotes Female Entrepreneurship. Standard data cleaning and processing were done using Python.

## 3.2 Multiple Linear Regression

To find the determinants of loan size under the DCA program, we will run an ordinary least squares (OLS) multiple linear regression. Since loan sizes under the DCA program follow an exponential distribution, we will run our regression models on the natural log of the loan amount (See A.1). As a result, we will usually interpret our regressions often as a percent change in loan amount (See A.2). In determining the best regression model, a forward selection algorithm was used to find the most important variables to reduce the residual sum of squares.

Missing data were handled by dropping or by replacing with the default value, which we will specify. Multicollinearity was checked using an informal approach described in A.3. Otherwise, the procedure is standard, and our models are presented in Section 5.

### 3.3 Tree-Based Machine Learning

Tree and forest models were trained following standard algorithms. These models are more have higher predictive power, but less interpretability, and will be used to corroborate our results from our regressions. A more in-depth explanation is in the source code available in the appendix (See A.4).

# 4 Summary Statistics and Visualizations

**Table 1:** Summary Statistics I

| | Observations | Mean | Std. Dev. | Min | Median | Max | Sum |
|---|---|---|---|---|---|---|---|
| Loan Amount (USD) | 164k | 11.6k | 304k | 0.0025 | 981 | 80.6M | 1.90B |
| Is First Time Borrower? | 90.5k | 0.547 | 0.498 | 0.0 | 1.0 | 1.0 | 49.5k |
| Is Woman Owned? | 90.5k | 0.320 | 0.466 | 0.0 | 0.0 | 1.0 | 28.9k |

*Note:* k: Thousand, M: Million, B: Billion

**Table 2:** Summary Statistics II

| | Observations | Unique | Most Frequent | Frequency |
|---|---|---|---|---|
| Region Name | 164k | 6 | Latin America & The Caribbean | 127k |
| Business Sector | 156k | 15 | Agriculture | 62.8k |
| Business Size | 31.1k | 5 | 1–5 | 26.8k |

*Note:* k: Thousand, M: Million, B: Billion

Table 1 and 2 show the summary statistics for the primary variables of interest. Is First time Borrower? and Is Woman Owned? are Boolean variables, meaning 1.0 indicates true, and 0.0 indicates false. Business Size is measured as the number of employees. Some immediate results to highlight are:

- Median loan amounts are significantly smaller than mean loan amounts. This indicates the data is positively skewed as shown in A1.
- 1.9 Billion USD in loans were backed by this program (does not mean 1.9 Billion Dollars was spent).
- 54.7% of loans (after 2008) was to first time borrowers, so it seems the majority of loans are to businesses that are disregarded by the banking system.
- 32.0% of loans (after 2008) were to women entrepreneurs.
- The most common loan was to businesses in the Latin America region, accounting for 77.4% of loans. This indicates there is a certain level of region-based bias in the program.
- For the data available, 86.2% of the business was a very small business with under 5 employees.

While we have 164,000 loan observations, other variables have many missing observations. For the Is First Time Borrower? and Is Woman Owned? variables, we dropped missing rows whenever we ran our analysis, while for Business Sector and Business Size, we filled them with the most frequent values. The former approach ensures our analysis is not skewed when comparing first time borrowers and woman owned businesses, compared if we filled them with values. The latter approach skews our data (but only slightly since 1–5 business sizes are 82.6% of businesses), and we can use a larger set of our data for later analysis.

### 4.1 Region Name

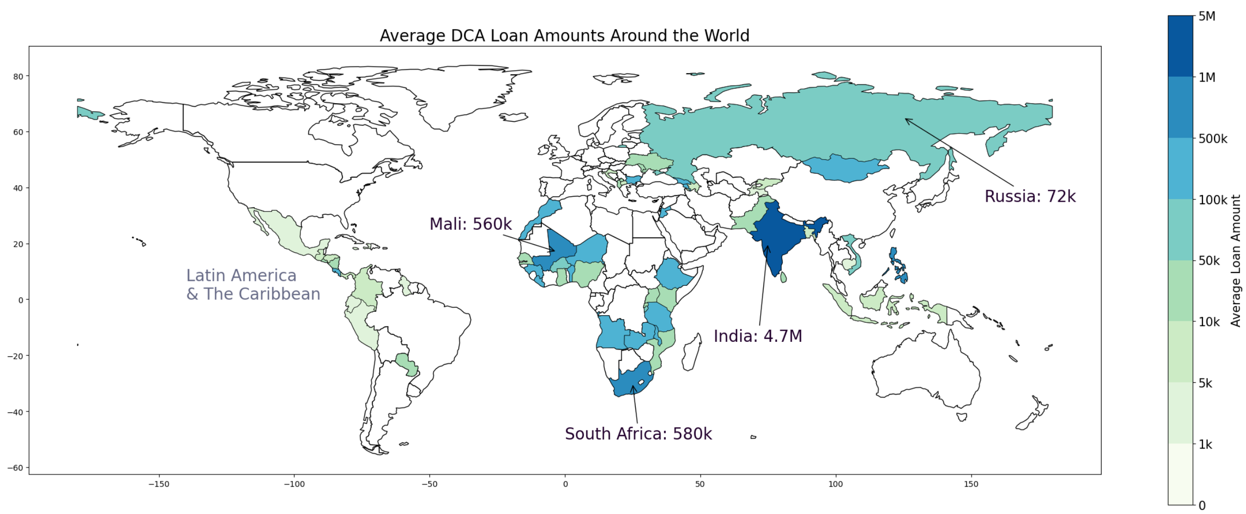


**Figure 1:** Above is the average loan amount backed by the DCA for countries with more than 10 loans. Countries that were excluded and where the DCA did not operate are in white. On the map, we highlighted countries with the highest average loan amounts. India is an extreme outlier with the average loans backed by the DCA being 4.7 Million USD.

Figure 1 summarizes where the DCA operates in the world. One interesting fact to note is the lack of any blue areas in Latin America & the Caribbean areas. Loans in the countries in this region on average are well under 50,000 USD. Loans to this region are the most common yet the smallest.

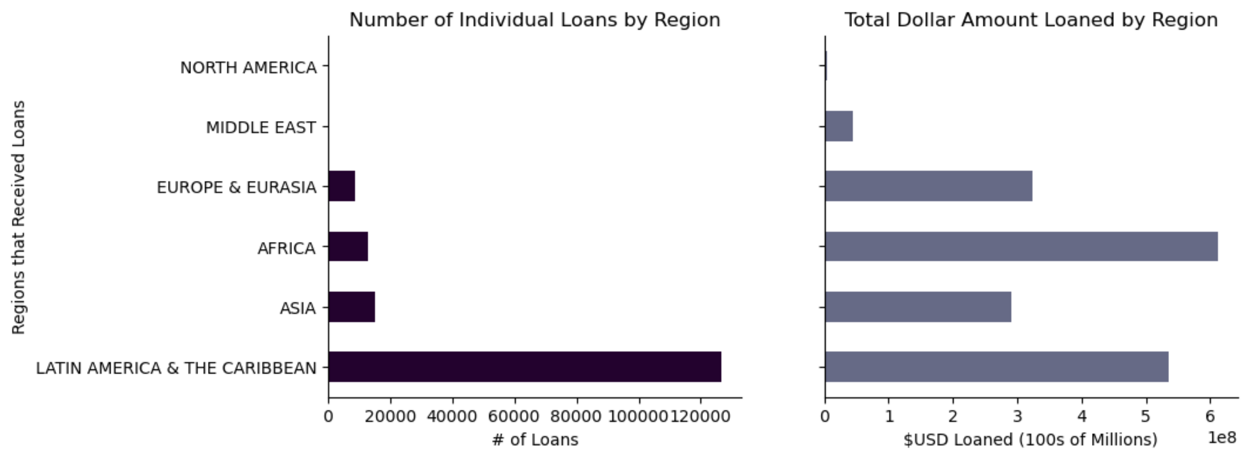


**Figure 2:** Above is a comparison between the frequency and total amount of loans by region.

Figure 2 shows how loan distribution strategy varies by region. Businesses in Latin America by far are the most frequent receiver of loans backed by the DCA. Yet on the right, Africa is ahead of Latin America in the total dollar amount of loans received. There seem to be signs of region-based patterns for loan distribution, which potentially indicates geopolitical motivations behind this program.

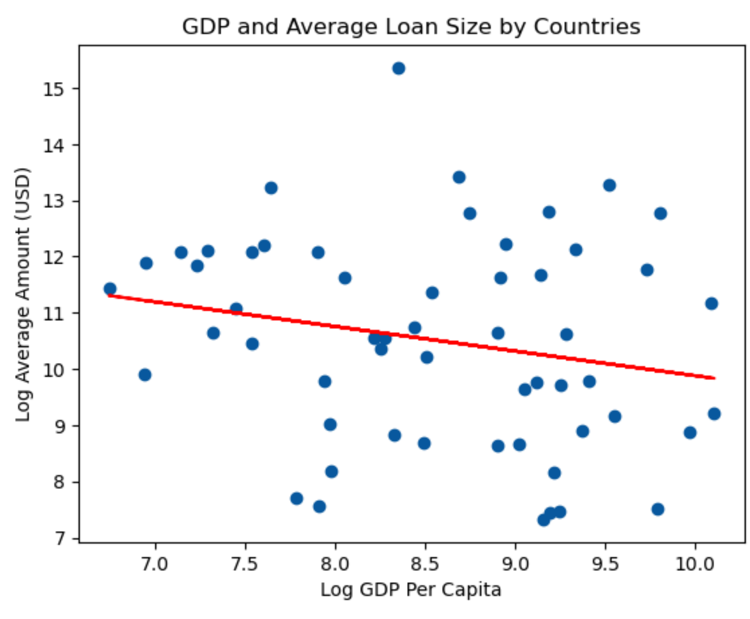


**Figure 3:** Above compares Log GDP Per Capita and Log Average Loan Amount for countries in the DCA dataset.

From Figure 3, these patterns seem independent of development need. There is a very weak negative correlation between development needs (measured by GDP Per Capita) and the size of loans. Countries that have higher GDP Per Capita have lower average loan amounts. This is a counter-intuitive result, since one would expect loans for businesses to get bigger as countries become richer and have bigger businesses.

One speculative explanation of this phenomenon could be that richer countries tend to have more developed financial institutions that operate in a less risky environment. Thus they are more willing to bear the risk to loan to smaller businesses of smaller amounts. Thus the DCA program would only need to step in to incentivize banks to give those very small loans, resulting in loans backed by the DCA program being very small in richer countries, and vice versa. This result means that the DCA program is doing its job of mobilizing credit for underserved markets and not simply funding loans that would have happened anyways!

## 4.2 Business Sector

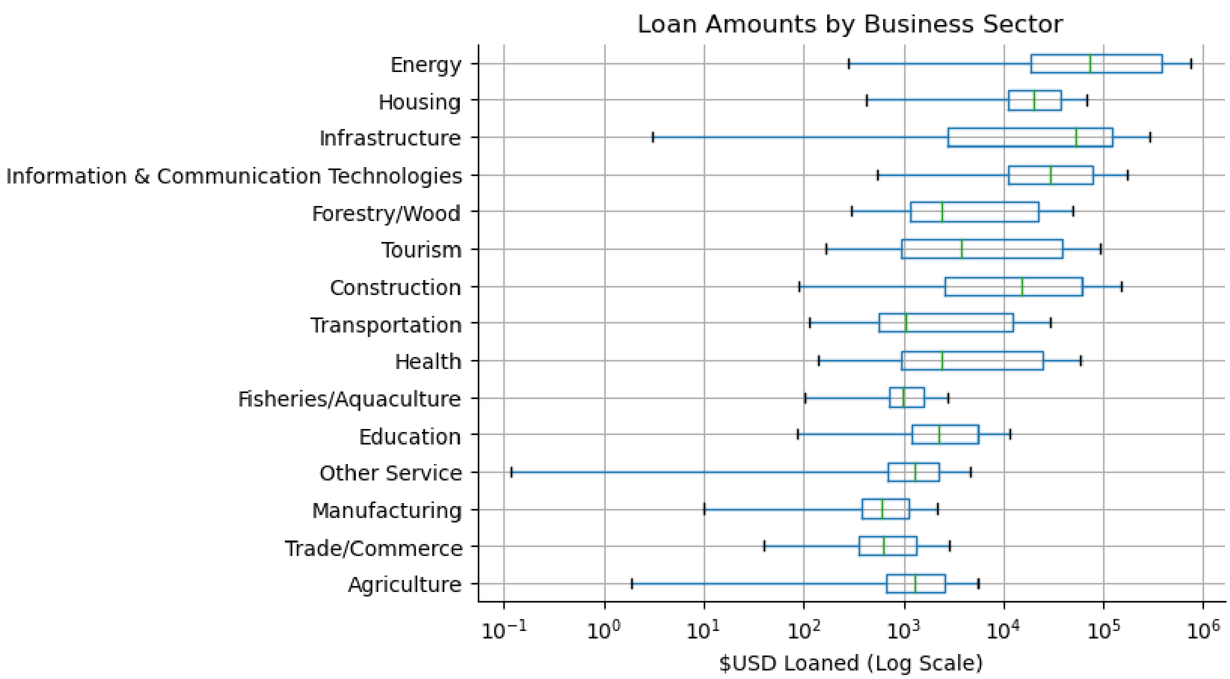


**Figure 4:** Above is a box plot of the Loan Amounts categorized by Business Sector. Sectors are sorted (from top to bottom) from least frequent, to most frequent. Note a log scale was used. Outliers are hidden to reduce visual clutter.

Unsurprisingly, there is a wide spread of loan sizes associated with business sectors (Figure 4). In theory, different business sectors require different types and levels of fixed capital investments. The Energy, Housing, and Infrastructure sectors have the highest median loan amounts in our dataset. There seems to be a negative correlation between the frequency of a specific loan to a sector and the median loan amount.

### 4.3 Business Size

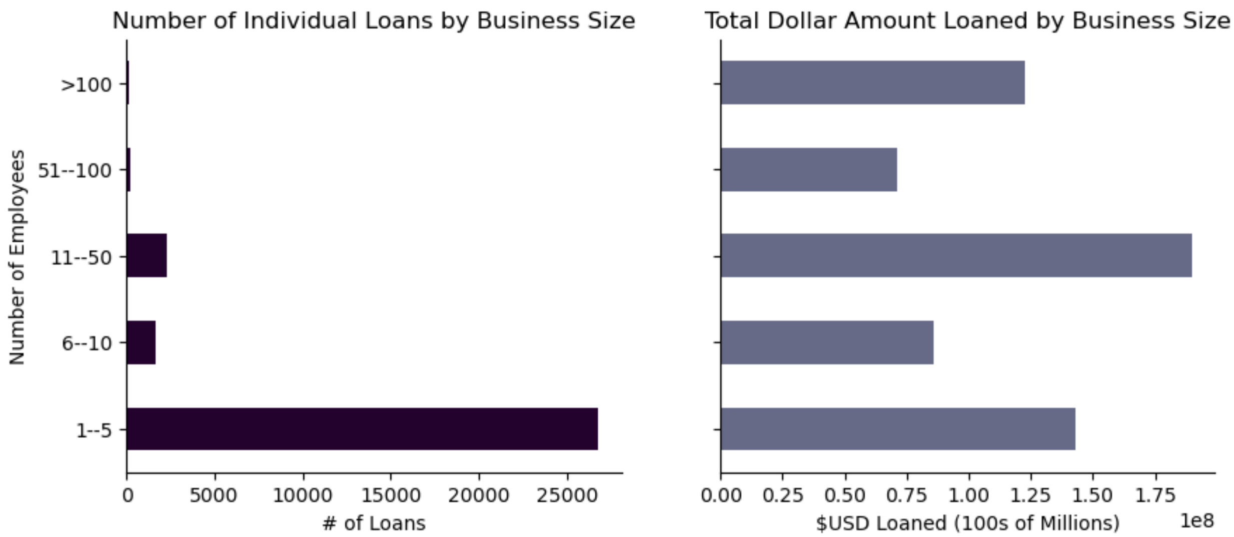


**Figure 5:** Above is a comparison between the frequency and total amount of loans by business size.

Another expected result is while smaller businesses received the most number of loans, bigger businesses received a higher dollar amount per loan on average (Figure 5). This is in line with a typical Cobb-Douglas production function since more units of labour requires more capital investment.

### 4.4 Is First Time Borrower?

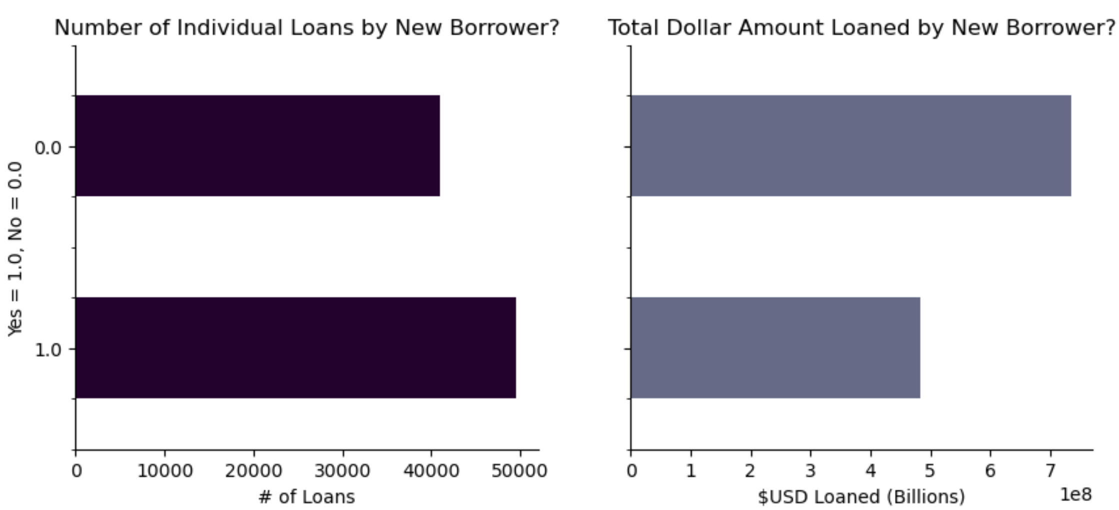


**Figure 6:** Above is a comparison between the frequency and total amount of loans by if First Time Borrower?

As discussed previously, new borrowers accounted for about half (54.7%) of the loans made out by the DCA. However, on average, they received less than former borrowers, accounting for a smaller proportion (39.7%) of the total amount of the loans paid. This effect is likely spurious (e.g. first time borrowers have smaller businesses resulting in smaller loans) since it is not an important variable in our regressions.

A clear direction for improvement for the DCA is to target more First Time Borrowers since the theory underpinning the program is lending to businesses typically overlooked by the banking system.

## 4.5 Is Woman Owned?

### 4.5.1 Gender Disparity of Loan Frequency

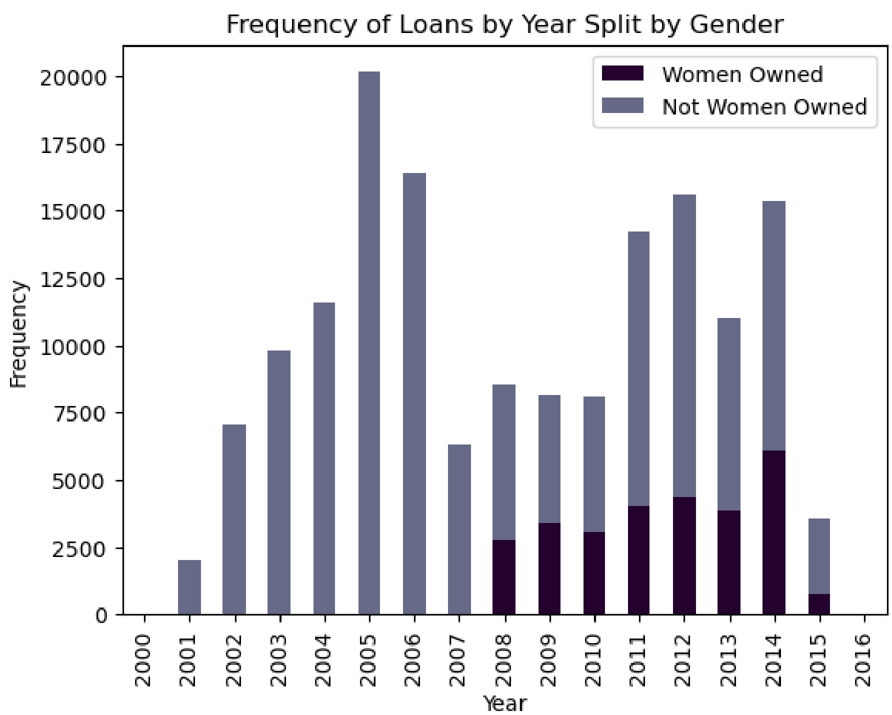


**Figure 7:** Above we plotted the number of loans backed by the DCA in each year in our dataset, split by gender. Before 2008, no gender data was available. Note that the years 2000 and 2016 seem to have no loans, but there are 4 and 5 loans in total respectively.

From Figure 7, we see that throughout the DCA loan program's history, women receive fewer loans than men. Before 2008, no gender was available, so women loans is not plotted. This comparison is misleading however, since this gap may be a reflection of pre-existing inequality.

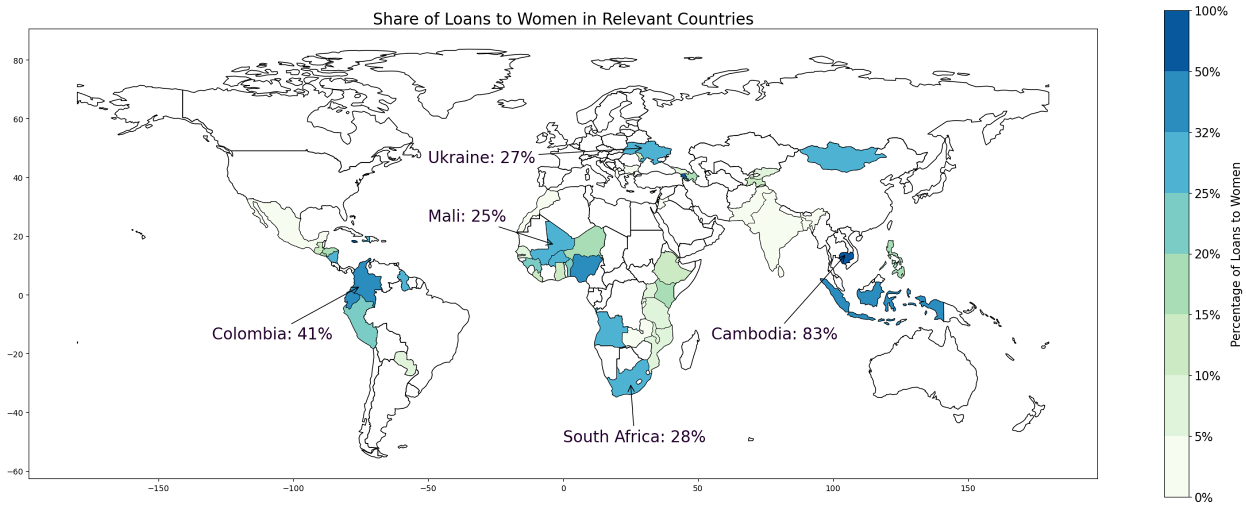


**Figure 8:** Above is the map of the percentage of loans backed by the DCA that are to women for countries with more than 10 loans. Countries that were excluded and where the DCA did not operate are in white.

Indeed, from Figure 8, we see that the percentage of loans going to women depends on the country. Cambodia and countries in Southeast Asia stand out as the highest lenders to women. Unfortunately, most regions loan to women at rates well below the 25% mark, below the dataset average (32%).

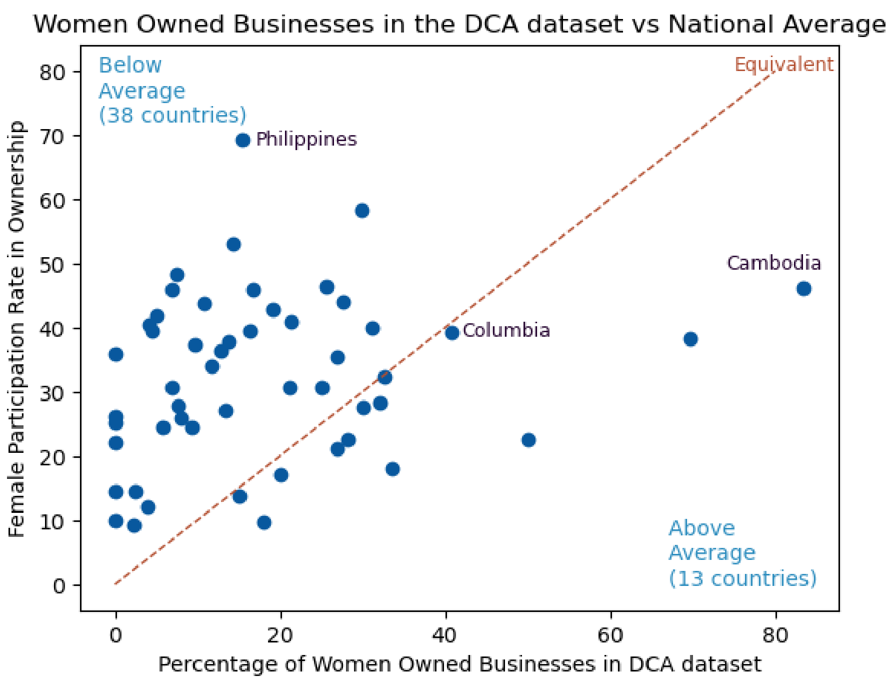


**Figure 9:** Above is the Percentage of Loans in the DCA dataset that was to woman against the national female participation rate in business ownership. “Equivalent” indicates these are equal.

Since the norms and gender equality and the entrepreneurship rates for women vary by country, it would be more interesting to evaluate the DCA by looking at how the DCA loans compare to the status quo (Figure 9). Assuming loans were randomly distributed, we would countries to be on the "Equivalent" line (i.e. loan share to women matches business ownership by women). Clearly, the majority of loans given out by the DCA program are below the national average. This might highlights a systemic issue with the DCA program: Loans are going disproportionately to businesses owned by men, even in comparison to the national average!

There are limitations with this comparison, however. The Female Participation Rate measures if a woman is among the "principal owners" business, so a business owned by men could still be counted as "women owned". On the other hand, the DCA's definition of a "women owned" business is unclear. Nevertheless, since the majority of businesses are small so have only one owner, the effect of this may be limited. Also, loans are not distributed randomly to businesses, but may depend on size and sector etc.

#### 4.5.2 Gender Loan Gap

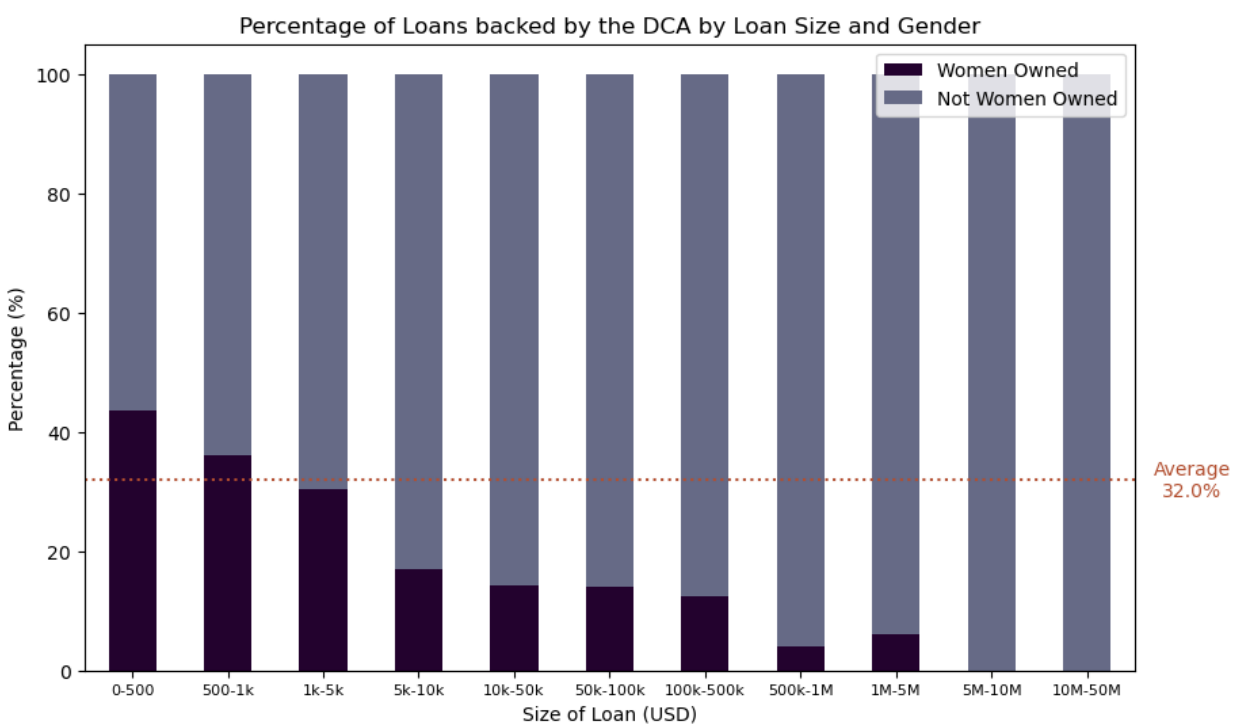


**Figure 10:** Above is plotted the percentage of DCA loans of increasing sizes going to women.

Not only do women receive loans at a rate below their participation rate in business ownership, but also the types of loans they receive also look drastically different from men. 32.0% of DCA loans go to women, so if they were distributed independently of gender we would expect the share of loans across loan sizes to be close to this average. However from Figure 10, only loans under five thousand dollars meet this expectation, and we see a significant drop off thereafter, with no loans greater than five million dollars going to women.

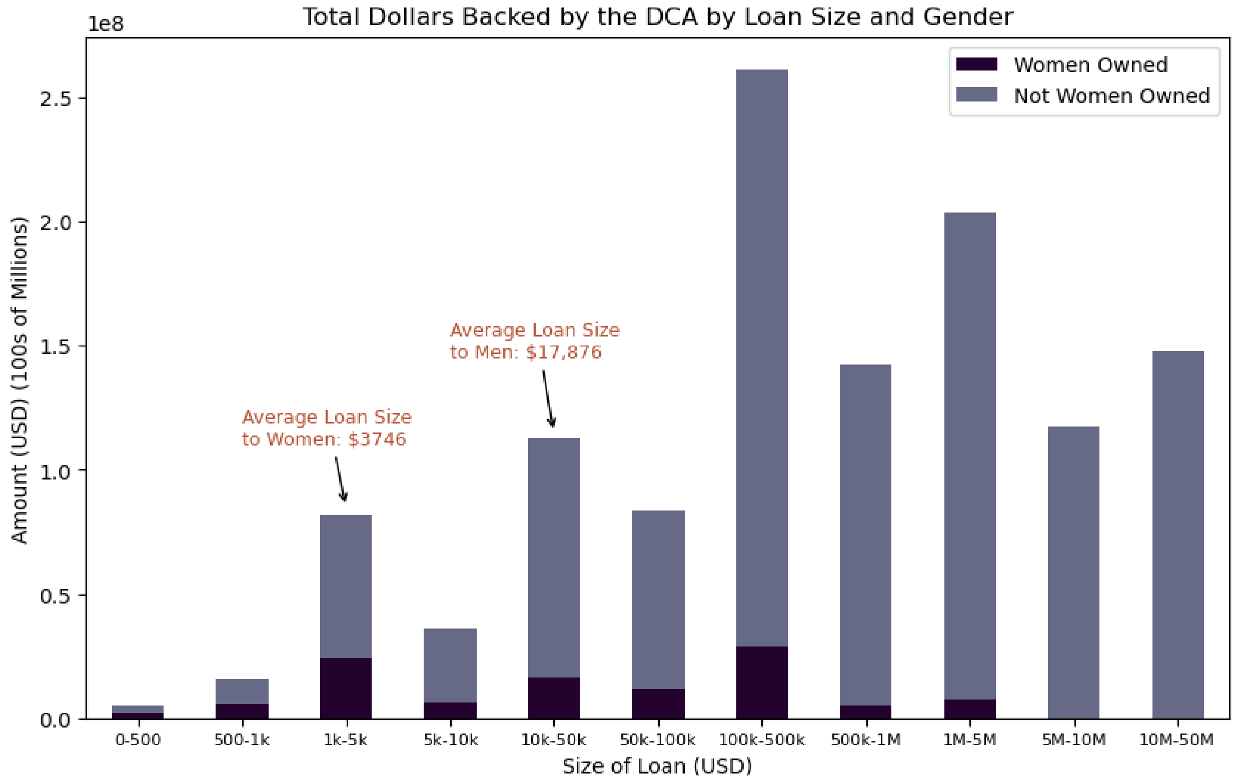


**Figure 11:** Above is the total loan dollars backed by the DCA separated by loan size and gender.

Of the 1.9 Billion dollars of loans backed by the DCA, despite 32.0% of loans going to women, only 9% of loan dollars ended up for women (dark purple), and 91% of loan dollars went to men (light gray). The reason why is clear: women entrepreneurs receive almost none of the loans larger than 500k, which roughly make up half of to total dollars of loans backed by the DCA. This will result in a ”Gender Loan Gap” meaning women receive smaller loans than male entrepreneurs. Henceforth, we will define the ”Gender Loan Gap” or simply ”Gender Gap” as the percentage difference in average (mean) loan amounts women entrepreneurs receive compared to men. Formally:

$$\text{Gender Gap} = \frac{\text{Mean Loan Amount}_{women} - \text{Mean Loan Amount}_{men}}{\text{Mean Loan Amount}_{men}} \times 100$$

An equal world is where the Gender Gap is 0%. Negative numbers mean women receive smaller loans than men. We will also define the Gender Equality Index (GEI) derived from the Gender Inequality Index (GII):

$$GEI = 1 - GII$$

Thus on the GEI scale, 1 means perfect equality, with smaller numbers between 0-1 meaning more inequality.

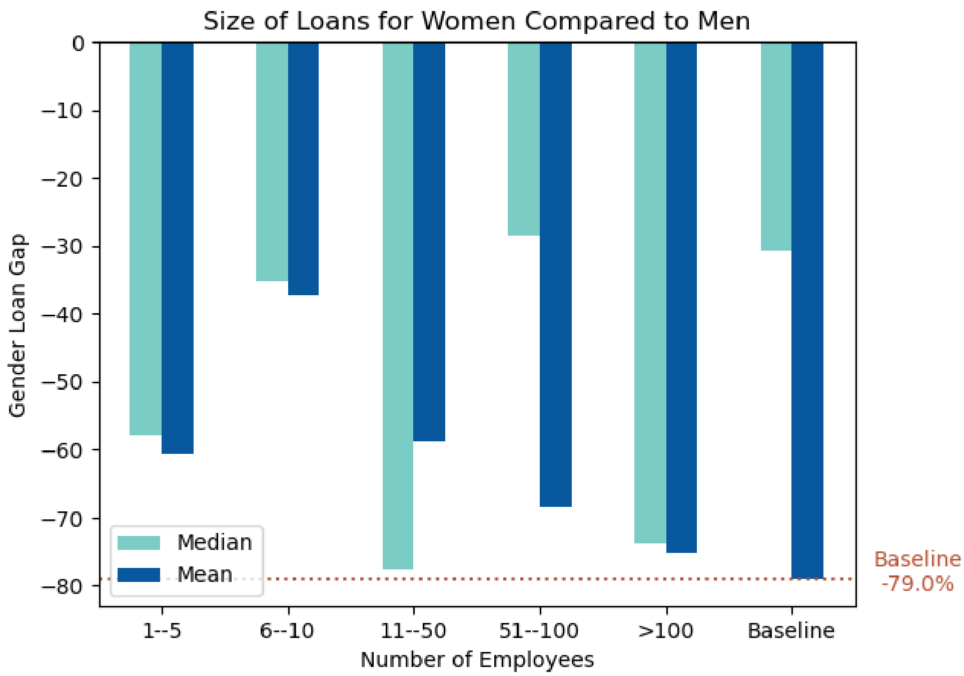


**Figure 12:** Above is plotted Gender Loan Gap for different sizes of businesses.

To prove that it is unlikely that women receive smaller loans because of some of the spurious relationships (i.e. women simply have smaller businesses resulting in smaller loans), see Figure 12. When we control for business size, women still systemically receive smaller loans than men. This gap seems to get worse as the business gets bigger, with large businesses (>100) owned by women receiving on average 75% smaller loans than businesses of comparable sizes owned by men. However, controlling for business size seems to have reduced the Gender differences across the board, so potentially if we include more variables, this relationship could still be spurious. We will test more rigorously in the regressions section.

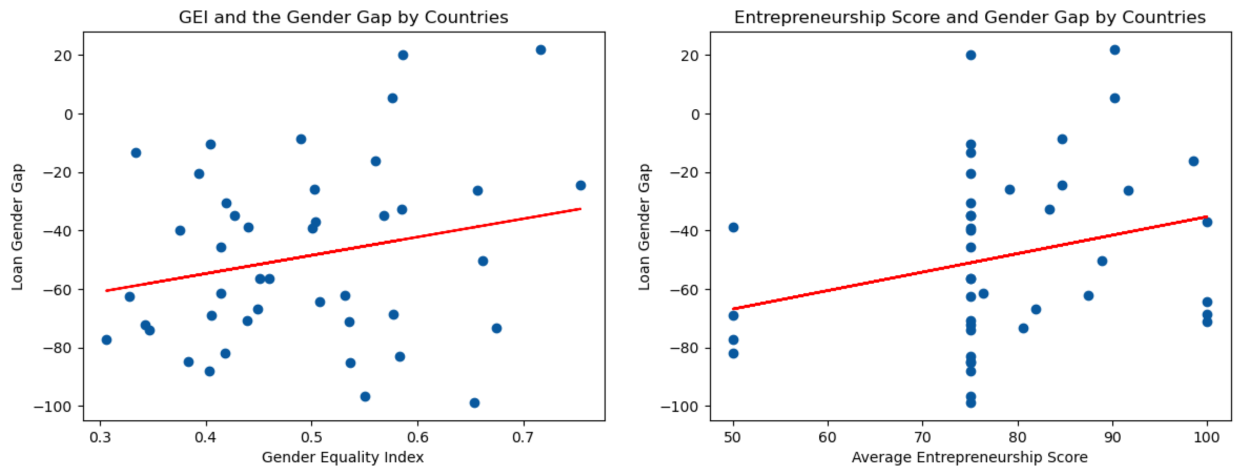


**Figure 13:** Above is the relationship between the GEI and Entrepreneurship Score. Note we dropped two extreme outliers Kyrgyzstan and Benin with gender gaps > +60%

There is a slight positive correlation between the GEI and the Entrepreneurship Score with Gender Gap. As countries are more equal as measured by these indicators, the Gender Loan Gap gets smaller (less negative). This correlation indicates that the gender loan gap in part is a reflection of systemic inequality.

### 4.6 Summary of Visualizations

From our visualizations, we found:

- Loan quantity and average loan size vary greatly by region and country. This is not well explained by development need (GDP per Capita), so there are other (likely political) influences.
- Loan quantity and loan size vary greatly by business sector and business size.
- New borrowers receive smaller loans on average, and make up about half of DCA loans.
- 32.0% of DCA loans go to women. While this number varies by country, in the majority of countries, the loan rate to women tracks below the number of women owned businesses.
- Bigger loans tend to go to men, resulting in a Gender Loan Gap. This Gender Gap persists across business sizes and is correlated with gender equality indexes.

# 5 Results

## 5.1 Regressions Including Gender Data

**Table 3:** Converted Regression Including Gender Data

| *$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$* | *Dependent variable: Loan Amount (USD)* | | |
|---|---|---|---|
| | Top 3 | Top 7 | Top 10 |
| Latin America & Caribbean | -62.26$^{***}$ | -61.59$^{***}$ | -63.19$^{***}$ |
| | (0.95) | (1.05) | (1.06) |
| 11-50 Employees | 946.69$^{***}$ | 992.36$^{***}$ | 1115.73$^{***}$ |
| | (2.66) | (2.57) | (2.58) |
| 6-10 Employees | 612.31$^{***}$ | 626.74$^{***}$ | 665.81$^{***}$ |
| | (3.11) | (3.00) | (2.99) |
| >100 Employees | | 11497.44$^{***}$ | 11087.33$^{***}$ |
| | | (9.93) | (9.87) |
| 51-100 Employees | | 4724.82$^{***}$ | 4683.11$^{***}$ |
| | | (8.32) | (8.27) |
| Asia | | -28.36$^{***}$ | -30.22$^{***}$ |
| | | (1.78) | (1.77) |
| Woman Owned | | -27.33$^{***}$ | -26.05$^{***}$ |
| | | (0.86) | (0.86) |
| Education | | | -68.01$^{***}$ |
| | | | (4.38) |
| Manufacturing | | | 11.07$^{***}$ |
| | | | (1.82) |
| Infrastructure | | | 1200.51$^{***}$ |
| | | | (13.45) |
| Observations | 90,464 | 90,464 | 90,464 |
| $R^2$ | 0.23 | 0.28 | 0.29 |
| Adjusted $R^2$ | 0.23 | 0.28 | 0.29 |
| Residual Std. Error | 1.23(df = 90460) | 1.18(df = 90456) | 1.18(df = 90453) |
| F Statistic | 8822.91$^{***}$ | 5024.26$^{***}$ | 3678.09$^{***}$ |
| | (df = 3.0; 90460.0) | (df = 7.0; 90456.0) | (df = 10.0; 90453.0) |

**Table 3:** Above are the results of using forward selection on all our variables. Due to missing data, we are only able to use about 90,000 observations. The algorithm's top 3, 7, and 10 choices are in order from top to bottom. Note we applied our formula transformation to the regression coefficients (and standard errors) in the table, so we interpret these values as percentages and do not include the fixed effect in this table (see A.2). The reference categories are Africa for Region, Agriculture for Business Sector, 1-5 for Business Size, not women owned, and not a first time borrower.

The first model we present is our forward selection algorithm using all our variables. Unsurprisingly, the size of the business is among the best predictors of loan size. However, surprisingly whether the business is in Latin America & the Caribbean is the single best predictor of loan size in the DCA program. Asia is also our 6th best predictor. This aligns with the findings that loans to Latin America & the Caribbean were the most common and yet were significantly smaller than other regions. This commonality and substantial effect both contribute to the algorithm selecting this variable first. Indeed with just the three best variables, our linear regression has an r-squared of 0.23 which is quite substantial.

Remarkably, the gender of the entrepreneur still comes in as the 7th most important variable of the 30 variables we have. Clearly, gender has strong predicting power on the loan size, independent of many other important variables such as region and business size. Other important predictors seem to be many of the variables relating to the type of business applying for the loan. This is unsurprising from an economic intuition perspective (i.e. different businesses require different levels and kinds of capital investments), and from our previous visualizations of loan sizes by industry.

However, it seems like adding these predictors does very little in increasing the r-squared coefficient (or reducing the Residual Std. Error). Thus, given the substantial prediction power of the top 7 specification (r-squared: 0.28), its simplicity compared to other specifications we have looked at, and that it includes the Woman Owned variable, in the context of finding the determinants of loan size with an emphasis on the Gender Gap, the top 7 specification is our preferred specification.

If we convert our model back into Log of Loan Amount (USD), our preferred model (top 7) can be explicitly written using values from the original (non-converted) regression table (See A.4):

$$\ln \hat{y} = 8.04 - 0.96x_1 + 2.39x_2 + 1.98x_3 + 4.75x_4 + 3.88x_5 - 0.33x_6 - 0.32x_7$$

- $\hat{y}$: Estimated Loan Amount (USD)
- $x_1$: Latin America & Caribbean (dummy)
- $x_2$: 11-50 Employees (dummy)
- $x_3$: 6-10 Employees (dummy)
- $x_4$: >100 Employees (dummy)
- $x_5$: 51-100 Employees (dummy)
- $x_6$: Asia (dummy)
- $x_7$: Woman Owned (dummy)

Using our model of choice, the Top 7 variables specification, we can interpret the following results:

- Region is an important determinant of loan size in the DCA program. Loans to Latin America & the Caribbean are over 62% smaller and loans to Asia are 28% smaller than other countries.
- Business Size is an important determinant of loan size in the DCA program. Compared to loans for businesses with 1-5 employees, loans are:
  - 6-10 employees: 6.3 times bigger
  - 10-50 employees: 9.9 times bigger
  - 51-100 employees: 47 times bigger
  - >100 employees: 115 times bigger
- Loans to women owned businesses are 27% smaller, independent of these previous variables.
- The business sector results in loans of vastly varying quantities which is supported by the previous visualizations. However, the explanatory power of this variable is very small.
- From running a bigger regression (See A.4), we found whether the business is a first time borrower has a negligible effect on loan size (<1%).

These results corroborate our previous data visualizations. Notice the estimated gender gap is significantly smaller than previous estimates since we have controlled for more variables. This gap cannot be directly attributed to gender-based discrimination or a causal effect (see A.5) and is a correlation result. However, a -27% difference in loan sizes is very substantial and the DCA program should do further qualitative analysis with more data on why this gap exists, and how to address these issues to support female entrepreneurs.

Business Size and sector have, as expected, large effects on loan size, as economic theory would imply. Also, the result that first time borrowers have a negligible effect on loan size is a positive result for the DCA, meaning it is achieving its goals of getting proper bank loans to new borrowers. An interesting result is the effect of Region on loan size, and we will revisit it in Section 6.

## 5.2 Regressions Excluding Gender Data

**Table 4:** Converted Regression Excluding Gender Data

| *$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$* | *Dependent variable: Log Loan Amount (USD)* | | |
|---|---|---|---|
| | Top 3 | Top 7 | Corrected Top 7 |
| Latin America & Caribbean | -77.21$^{***}$ | -76.96$^{***}$ | -73.27$^{***}$ |
| | (0.94) | (0.91) | (0.89) |
| Asia | -52.71$^{***}$ | -56.04$^{***}$ | -50.22$^{***}$ |
| | (1.32) | (1.26) | (1.25) |
| Trade/Commerce | -38.16$^{***}$ | -32.91$^{***}$ | -36.52$^{***}$ |
| | (0.65) | (0.62) | (0.61) |
| 11-50 Employees | | 791.24$^{***}$ | 903.38$^{***}$ |
| | | (2.48) | (2.49) |
| 6-10 Employees | | 510.61$^{***}$ | 550.25$^{***}$ |
| | | (2.95) | (2.97) |
| Female Participation Rate in Ownership | | 2.94$^{***}$ | |
| | | (0.04) | |
| >100 Employees | | 9151.41$^{***}$ | 10798.97$^{***}$ |
| | | (9.64) | (9.71) |
| 51-100 Employees | | | 4766.53$^{***}$ |
| | | | (7.97) |
| Observations | 148,949 | 148,949 | 148,949 |
| $R^2$ | 0.20 | 0.29 | 0.28 |
| Adjusted $R^2$ | 0.20 | 0.29 | 0.28 |
| Residual Std. Error | 1.19(df = 148945) | 1.11(df = 148941) | 1.12(df = 148941) |
| F Statistic | 12427.16$^{***}$ | 8858.08$^{***}$ | 8442.58$^{***}$ |
| | (df = 3.0; 148945.0) | (df = 7.0; 148941.0) | (df = 7.0; 148941.0) |

**Table 4:** Above are the results of using forward selection, excluding gender and first time borrower data. This allows us to use about 150,000 observations. The algorithm's top 3 and 7 choices are in order from top to bottom. Corrected Top 7 replaced Female Participation Rate in Ownership because of multicollinearity with the next best variable. Note we applied our formula transformation to the regression coefficients (and standard errors) in the table, so we interpret these values as percentages and do not include the fixed effect in this table (see A.2). The reference categories are Africa for Region, Agriculture for Business Sector, and 1-5 for Business Size.

The second model we present is our forward selection algorithm excluding gender and first time borrower data. The main purpose of this model is to validate the results of our previous model with more observations. The resulting model is very similar to our previous model, although 'Asia' and 'Trade/Commerce' increased in importance. Converting back into the Log of Loan Amount (USD), our preferred model (Corrected top

7) can be explicitly written using values from the original (non-converted) regression table (See A.4):

$$\ln \hat{y} = 8.30 - 1.32x_1 + 2.31x_2 + 1.87x_3 + 4.69x_4 + 3.88x_5 - 0.70x_6 - 0.45x_8$$

- $\hat{y}$: Estimated Loan Amount (USD)
- $x_1$: Latin America & Caribbean (dummy)
- $x_2$: 11-50 Employees (dummy)
- $x_3$: 6-10 Employees (dummy)
- $x_4$: >100 Employees (dummy)
- $x_5$: 51-100 Employees (dummy)
- $x_6$: Asia (dummy)
- $x_8$: Trade/Commerce

Variables are not in order of importance, and instead, use the same naming convention as the previous regression for easy comparison. Notice how the parameters of the variables are very similar to the previous model: $\ln \hat{y} = 8.04 - 0.96x_1 + 2.39x_2 + 1.98x_3 + 4.75x_4 + 3.88x_5 - 0.33x_6 - 0.32x_7$.

- Region is an important determinant of loan size in the DCA program. Loans to Latin America & the Caribbean are over 73% smaller and loans to Asia are 50% smaller than other countries.

- Business Size is an important determinant of loan size in the DCA program. Compared to loans for businesses with 1-5 employees, loans are:

  - 6-10 employees: 5.5 times bigger
  - 10-50 employees: 9.0 times bigger
  - 51-100 employees: 48 times bigger
  - 100 employees: 108 times bigger

Which are more or less the same values as previously found. However, the negative effect of Asia increased from -28% to -50%. Since Asia tends to have the most women loans (See Figure 8), this bigger effect may be simply because this model does not control for gender. So, the negative gender effects may be lumped into the Asia dummy variable.

Also to note, in this model, whether the business is in Trade/Commerce sector has the 3rd highest explanatory power of all our variables. However, if you recall that Trade/Commerce was the 2nd most common loan type (See Figure 4), this explains why this variable is so important. Trade/Commerce businesses are predicted to receive 37% smaller loans than other business sections. Other business sector variables result in vastly varying quantities from the coefficients. However, the explanatory power of these variables is very small (r-squared improvement of $<0.04$) (See A.4).

### 5.3 Machine Learning Including all Variables

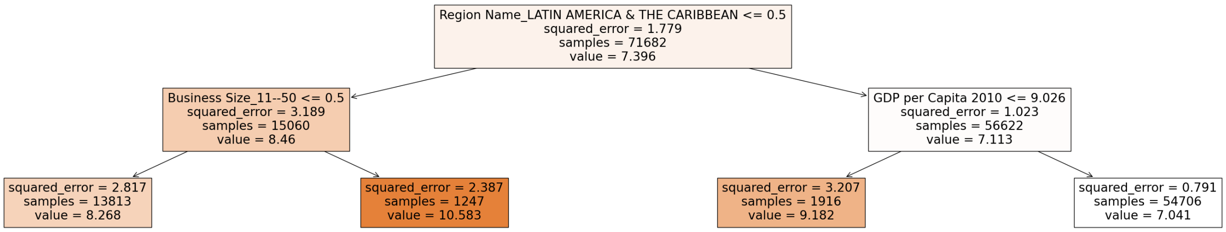


**Figure 14:** Above is the tree obtained by from regressing our observations using a simple tree algorithm (See A.4). $MSE = 1.27$, $R^2 = 0.28$

Using Machine Learning, we can gain insights into how our linear model compares to better prediction algorithms. One major advantage of using tree-based ML models is we no longer have to worry about multicollinearity problems. Trees can capture non-linear interactions between variables, and are immune to correlations between variables! The trade-off is that interpreting our model will become much more difficult.

Figure 14 is the result of regressing our values using a simple tree algorithm described in A.6. Like our linear regression, the decision tree agrees splitting on the Latin America region is highly predictive of the final loan size. Converted to non-logged terms, loan sizes in Latin America are on average $1,200, yet in other regions are on average $4,700. This approximately 75% reduction in loan size is in line with previous regressions. After this split, the tree splits using the variable Businesses with 11-50 employees. Businesses of this size have much bigger loans than the average loans of businesses of other sizes. Again this is not a surprise and is in line with our previous regressions.

However, it is a surprise to see GDP per Capita in 2010 to be a strong predictor in the right subtree. It seems by splitting on GDP per Capita is less than 8,300 (9.03) for regions in Latin America can split off many outliers which have extremely large loans for the region $9,700 (9.18), about 8 times the average for the region. It seems like the tree is overfitting the data.

For such a simple model, the performance is very good with a medium R-squared and a small Mean Squared Error. The R-squared of this model is comparable to our linear regression models! For more prediction power, we trained our data using Random Forests as shown in Figure 15.

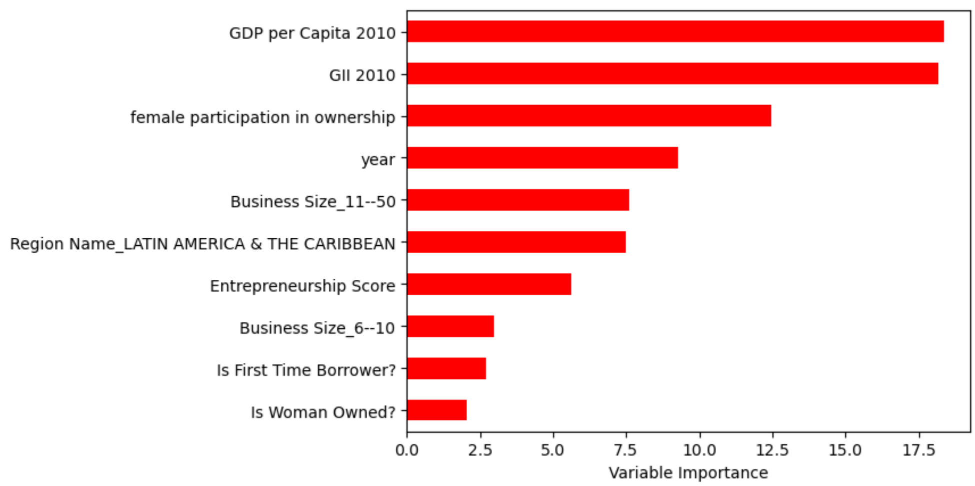


**Figure 15:** Above is the top 10 most important variables using a Random Forest Algorithm on all variables (See A.4 for source code). It was trained and validated on an 80/20 train/test dataset. $MSE = 0.59$, $R^2 = 0.66$

From Figure 15, we see some surprising results. The top 4 most important variables the forest splits on are "GDP, GII, Female Participation Rate in Ownership, and year", none of which showed up in our previous regressions. This suggests there is a highly non-linear relationship between loans and these variables.

However, notice how 3 of these 4 variables are national indicators. Combined with our observation in our simple tree, where GDP is used to split a section of outliers in a specific region, it seems like our forest is using these national indicators to reverse-engineer specific countries! Since these indicators are a unique identifier of a country (e.g. no two countries have the same GDP) it makes sense to instead of using the previously very powerful Region Name dummies, simply split until we have divided our loans into different countries! While we cannot definitively prove what is going on in this forest, this is a highly plausible conjecture considering everything we already know.

This result has some interesting implications. Recall in the introduction, literature has shown that foreign aid is influenced by political interests and strategy. This tree model reveals the importance of the specific country (not just region) on loan size, indicating that perhaps the DCA program is influenced by these political interests, which vary by country too.

### 5.4 Machine Learning Excluding Indicators, Including Gender Data

Our previous tree models were cheating a little. By splitting the data into countries, and so factoring in the varying levels of political interest they are to the US, the trees were able to make better predictions. The relationship between these country indicators and the political interest of the US is likely extremely non-linear, which explains why our linear models were unable to use these indicators effectively. We will force the tree model to not use these indicators, so we can compare it to our linear regression models.

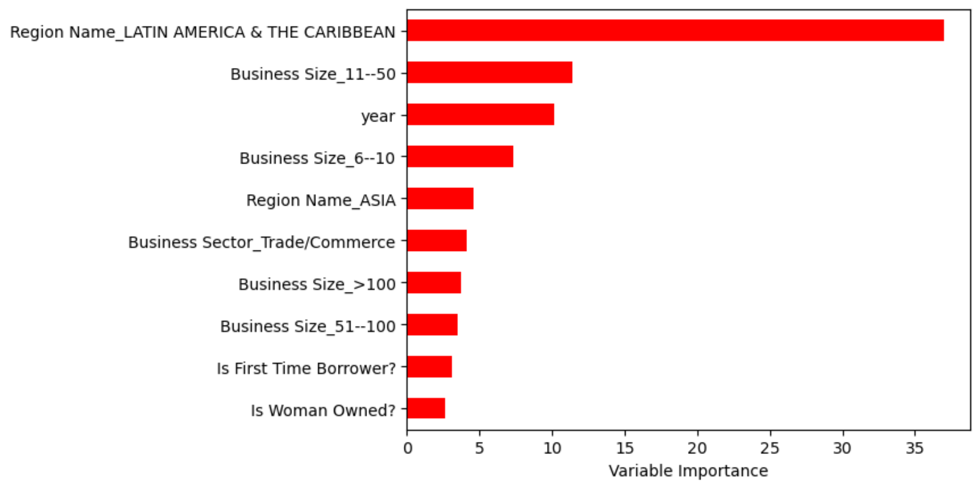


**Figure 16:** Above are the top 10 most important variables using a Gradient Boosted Random Forest Algorithm, excluding country indicators (See A.4 for source code). It was trained and validated on an 80/20 train/test dataset and used a grid search algorithm for hyperparameter tuning. $MSE = 1.03$, $R^2 = 0.49$

In Figure 16 we present the results of using the state-of-the-art Gradient Boosted Random Forest. The importance of our variables seems to align much more closely with our previous linear regressions. Region dummies such as Latin America and Asia, and business sizes are very important predictors, as well as some business sectors. The Is Woman Owned? parameter appears 10th on our variable importance list, but it was the 7th variable using forward selection in regressions. Again, it year appears as a very important parameter that our linear regression model did not pick up on. Year probably is a very non-linear parameter as we will show in the next section.

A common way to better understand how our complex forest model is making predictions is using a partial dependence plot. Partial dependence plots show how the predicted outcome (Log Loan Amount (USD)) is affected by the parameter holding all other variables fixed at average levels. However, the interpretation can be hazardous since forests can capture non-linearities/interactions in our data, so "holding all other variables fixed at average levels" is a dangerous assumption, since the variable of interest could have a non-linear interaction with the other variables. Since essentially we are linearizing the forest's predictions, this is not a true representation of how the forest makes predictions but shows how the forest predicts on average. This is enough and will allow us to make interesting comparisons with our regressions (See A.4 for more discussion on partial dependence plots).

**Table 5:** ML Partial Dependence vs Regression Including Gender Data

| | 0 | 1 | Difference | ML (%) | Regression (%) |
|---|---|---|---|---|---|
| Latin America & Caribbean | 1.17 | -0.29 | -1.46 | -76.73 | -61.59 |
| 11-50 Employees | -0.05 | 1.78 | 1.83 | 524.46 | 992.36 |
| 6-10 Employees | -0.03 | 2.07 | 2.10 | 715.67 | 626.74 |
| >100 Employees | -0.01 | 3.72 | 3.73 | 4074.02 | 11497.44 |
| 51-100 Employees | -0.01 | 2.56 | 2.57 | 1202.44 | 4724.82 |
| Asia | 0.05 | -0.02 | -0.08 | -7.58 | -28.36 |
| Is Woman Owned? | 0.10 | -0.20 | -0.30 | -25.84 | -27.33 |

**Table 5:** Column 0/1 is the partial dependence plot at 0/1 (loan does/does not satisfy dummy variable). "Difference" is Column 1 - Column 0. Intuitively, it measures the average effect of satisfying the dummy variable on the log of loan size. "ML (%)" is the "Difference" column converted with our formula. "Regression" (%) are the results from Table 3, Top 7 specification.

A partial dependence plot is usually a plot like Figure 18, however, it can also be created for our dummy variables. Since there are only two points 0 and 1, they would all be uninteresting plots of lines of various slopes. Instead, we summarize these plots in Table 5 and compare them to our regressions.

Remarkably, all our results are roughly in line with our regressions, especially being a woman owned business has a -26% effect on loan size on average. In our ML model, there is a more muted effect of business size, and Asia in general compared to our OLS regression, but the effect of Latin America & the Caribbean is greater. This gives very strong evidence that our linear regression model is capturing the same kind of results as our highly predictive ML model.

## 5.5 Machine Learning Excluding Indicators and Gender Data

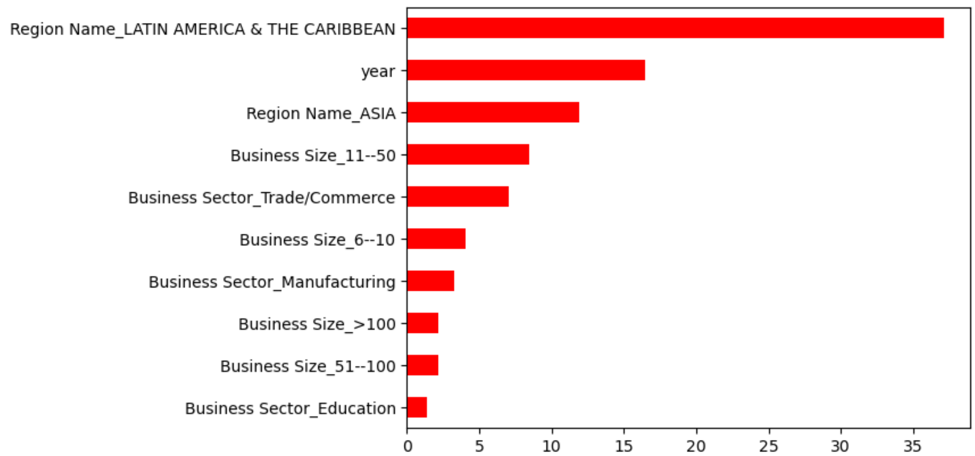


**Figure 17:** Above is the top 10 most important variables using a Gradient Boosted Random Forest Algorithm, excluding country indicators and Gender Data (See A.4 for source code). It was trained and validated on an 80/20 train/test dataset and used a grid search algorithm for hyperparameter tuning. $MSE = 0.98$, $R^2 = 0.49$

Finally, we ran the same algorithm on a dataset excluding both country indicators, gender, and first time borrower data. The main purpose of this model is to validate the results of Section 5.2. Figure 17 shows the importance of each variable in our forest. The importance of our variables seems to again align closely with our previous linear regressions. Region dummies such as Latin America and Asia, and business sizes are very important predictors, as well as some business sectors. Again, it year appears as a very important parameter that our linear regression model did not pick up on.

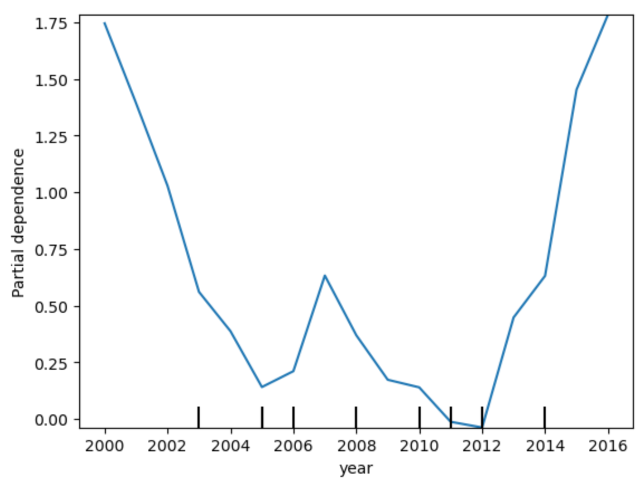


**Figure 18:** Above is the partial dependence plot for the variable year on Log Loan Amount (USD).

Since we have not dropped data before 2008 (because we excluded Is Woman Owned? etc.), Figure 18 shows how our model treats the year variable. It is a very nonlinear relationship.

**Table 6:** ML Partial Dependence vs Regression Excluding Gender Data

| | 0 | 1 | Difference | ML (%) | Regression (%) |
|---|---|---|---|---|---|
| Latin America & Caribbean | 1.16 | -0.28 | -1.44 | -76.25 | -73.27 |
| Asia | 0.13 | -0.14 | -0.27 | -23.77 | -50.22 |
| Trade/Commerce | 0.18 | -0.11 | -0.29 | -25.32 | -36.52 |
| 11-50 Employees | -0.03 | 2.30 | 2.33 | 929.97 | 903.38 |
| 6-10 Employees | -0.02 | 1.85 | 1.87 | 547.78 | 550.25 |
| >100 Employees | -0.00 | 2.71 | 2.71 | 1404.87 | 10798.97 |
| 51-100 Employees | -0.00 | 2.30 | 2.31 | 904.39 | 4766.53 |

**Table 6:** Regression (%) are the results from Table 4, Corrected Top 7. See Table 5 for details on other columns.

Table 6 summarizes the partial dependence plots of our dummy variables. Compared to our linear regressions, these values closely align with our regression results. For example, a business in Latin America on average receives -76% smaller loans, which is similar to our -73% achieved with the 'Corrected Top 7' specification in our OLS regression. Surprisingly, the effect of business size for businesses with more than 51 employees is significantly reduced compared to our OLS models. For example, the forest model estimates that a business with more than 100 employees receives 14 times bigger loans, but was estimated as 108 times bigger in our OLS model. Likely this is due to the fact of many non-linear interactions that mute this effect. Never the less, there is a substantial effect supported by the ML model. In general, we will opt for the regression model to interpret our results, since the interpreting the Machine Learning results linearly is hazardous as previously discussed.

# 6 Limitations and Future Research

The major limitation of our results is we were unable to conduct any causal analysis of our results. Thus, the estimated effects of our variables on loan size, especially gender, cannot be interpreted as causal (i.e. the gender loan gap is a result of discrimination). Although we have controlled for a large pool of relevant variables (i.e. business size, region), there are always unobserved variables that potentially are affecting our results. Further work can be done to solve the issues with performing Difference in Difference and Instrumental Variables as identified in A.5. It is likely that updated and novel data will be necessary to solve these issues.

Another limitation is the way we selected our regression features. While we employed a forward selection algorithm, which is sufficient for most purposes, it may not be the optimal algorithm for this problem. Improvements to our analysis can be made by implementing a better search algorithm.

Furthermore, filling in business sizes and business sectors with the most frequent values may have resulted in slight biases in our analysis as discussed in Section 4. However, this was a necessary step to run our regressions on a meaningful subset of our data, but perhaps there are better ways to handle this missing data yielding better results.

In addition, further work can be done on business sector data. Comparing whether DCA loan funds are going to neglected business sectors was unexplored, yet is an important question for evaluating the program.

Finally, our analysis was ultimately handicapped by the data available to us. Unresolvable missing data was a significant problem (see A.4), along with a narrow set of loan features and a limited time frame. There was no data available to us about the impacts of the loans, i.e. if it was repaid, how it was spent, and follow-up data with the borrower. With this data, we could run an interesting analysis of the impacts of the DCA program, instead of simply the patterns of DCA loans.

Nevertheless, by identifying the patterns behind the DCA loans, we can uncover clear shortcomings of the DCA program and potential avenues for improvement. Also, the unique approach of focusing on the loan outcomes for women is an uncommon, yet very important topic in developmental finance. Data for all development programs should include a gender dimension to evaluate its performance for those who are often neglected.

## 7 Conclusion

The data shows that the region, business size and sector, and the gender of the entrepreneur have significant effects on the final loan amount received by the borrower. Using OLS multiple regression models, we estimated these precise effects while controlling for other variables, and corroborated these results using state-of-the-art machine learning methods. From these results, we identified obvious improvements to the DCA program in the facets of 1. Reducing the influences of politics, 2. Stronger assessment of if DCA backed loans are going to businesses that would not have otherwise, and most importantly, 3. Increasing loans and loan amounts to women entrepreneurs.

Latin America & The Caribbean are favoured heavily by the DCA in terms of loan frequency, however, receive approximately 75% smaller loans than Africa (Regression: -73.27%, ML: -76.25%). Our machine learning model also detected high variability predicated by national indicators, indicating there are high discrepancies determined by nationality. This gives evidence of political conflicts of interest as identified in the literature (See Section 2.4). Unfortunately, this means that these political influences may be reducing the potential effectiveness of the DCA program. Ideally, the program should operate from a humanitarian perspective, maximizing positive impact irrespective of the country. However, this might be challenging for a program funded by the U.S. Government.

Our regressions estimate that the effects of business size on loan size are substantial. Compared to businesses with 1-5 employees, our regression model pins the effect as approximately 5.5 times bigger loans for businesses for 6-10 employees, 9 times for 11-50 employees, 48 times for 51-100 employees, and 108 times for >100 employees. This is not a surprising result and aligns with standard economic theory that larger businesses need more capital investment. We also found that very small businesses (1-5 employees), were heavily favoured by the DCA program (86.2 %) of all loan transactions, yet the majority of loan dollars went to larger businesses. It is hard to read too much into this result without better measures of whether the loan is going to a business that would not have gotten a loan otherwise. Would the banks have given these large loans to bigger businesses without the DCA? Or are banks simply taking advantage of the program to reduce their own liability?

Business Sector has a highly variable impact on loan size, as expected since different sectors have different business needs. However, our regression and machine learning models show that in general, these are not very strong predictors of loan size ($R^2 < 0.04$ for the regression). Trade/Commerce is the exception (2nd most frequent loan), with predicted to receive 36.5% smaller loans compared to Agriculture, which is the most frequent loan type, and also tends to receive smaller loans.

First time borrowers made up a slight majority of loans in the DCA program (54.7%). For a program specifically targeted to businesses underserved by banks, this is perhaps an underwhelming number. The DCA program should have a stronger criterion for evaluating whether along is going to a business that would not have gotten on otherwise. Positively, there is a negligible (<1%) difference in loan sizes between first time borrowers and former borrowers for comparable businesses.

Finally, the primary focus of this paper was uncovering the Gender Loan Gap (See 4.5.2 for definition). Not only does the DCA program give loans at a rate to women below the rate of women owned businesses for three-quarters of the countries in the program (Figure 9), the loans women receive are significantly smaller than men. Women rarely get loans larger than $5,000, and the larger the loan, the less likely it is to go to a woman (Figure 10). So although 32% of loans are to women in the program, only 9% of loan dollars go to women (Figure 11). Controlling for relevant factors such as region, business size, business sector, and year, still, yields that for businesses that are comparable in these dimensions, women owned businesses receive 26% smaller loans than men owned businesses (ML: -25.84%, Regression -27.33%).

The World Bank and other sources have extensively studied the importance of women entrepreneurs for sustainable development, and a USAID report has admitted that barriers do exist for women entrepreneurs, and "Promoting financial services to women is an important factor in improving women's access to entrepreneurship" (World Bank, 2012; Jazouli et al., 2020). It is disappointing there is no evidence that the DCA program is following through with these facts and is giving loans to women at a below status-quo rate and amount. Future programs in foreign aid and development need to emphasize keeping track of statistics for women and be held accountable for promoting gender equality.

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# Appendix

## A.1 Justification of Logarithmic Transformation

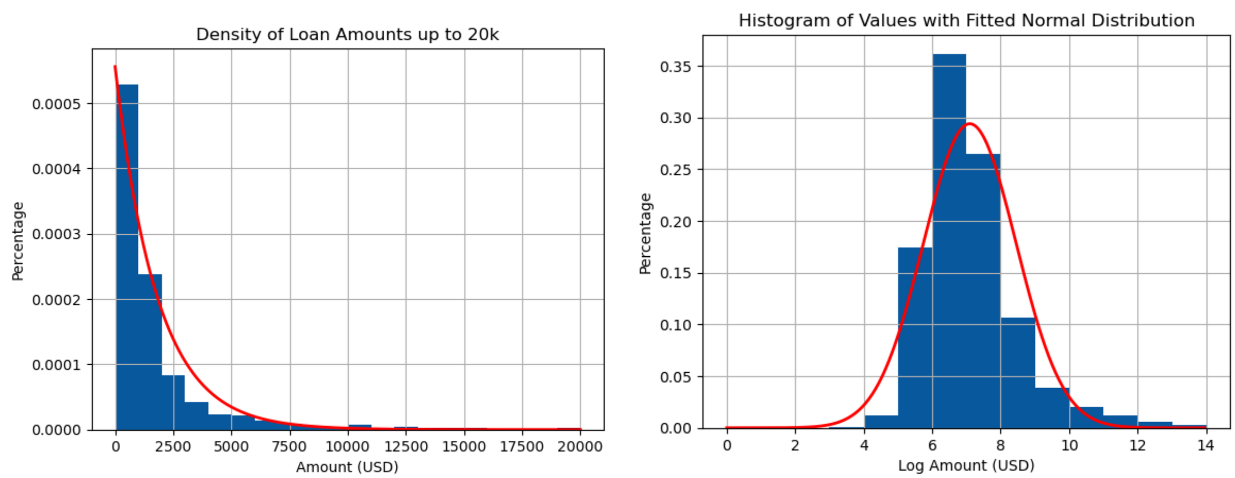


**Figure 19:** On the left is the density plot of loan amounts with a fitted exponential distribution. On the right, is the density plot of log loan amounts with a fitted normal distribution. Log loan amounts follows is roughly normally distributed, which will make our linear regressions perform better. A similar argument can be made for GDP per Capita.

## A.2 Interpretation of Logarithmic Transformation Results

Since we took the log of our dependent variable (y), the interpretation of our regressions will slightly be different. Let $\beta_0, \beta_1, \beta_2, ...\beta_n$ be the parameters of our regression with $n$ different independent variables (x). The linear regression gives us the estimator of $\ln \hat{y}$ as a function of realized $x$'s as shown below:

$$\ln \hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n$$

When interpreting linear regressions we assume everything is fixed except for one independent variable we are changing, say $x_i$. So, we define $\ln A = \beta_0 + \beta_1 x_1 + ... + \beta_{i-1} x_{i-1} + \beta_{i+1} x_{i+1} + ... + \beta_n x_n$ is a constant in the context of interpreting $x_i$. The previous equation simplifies to:

$$\ln \hat{y} = \ln A + \beta_i x_i$$

$$\hat{y} = A e^{\beta_i x_i}$$

Define $\hat{y}'$ to be the estimate where everything fixed except $x_i$ increases by one. The percent change in $\hat{y}$ is given as

$$
\begin{aligned}
\%\Delta\hat{y} &= 100 * \frac{\hat{y}' - \hat{y}}{\hat{y}} \\
&= 100 * \frac{Ae^{\beta_i(x_i+1)} - Ae^{\beta_i x_i}}{Ae^{\beta_i x_i}} \\
&= 100(e^{\beta_i} - 1)
\end{aligned}
$$

Thus, we can interpret our parameter $\beta_i$ using this formula as the percent change in the estimate of our dependent variable (y) given a unit increase in $x_i$. An important note is that our fixed effect $\beta_0$ cannot be interpreted using this formula since it does not have a corresponding $x_0$. This makes sense we are calculating percent change, and fixed effects by definition do not change.

### A.3 Preventing Multicollinearity

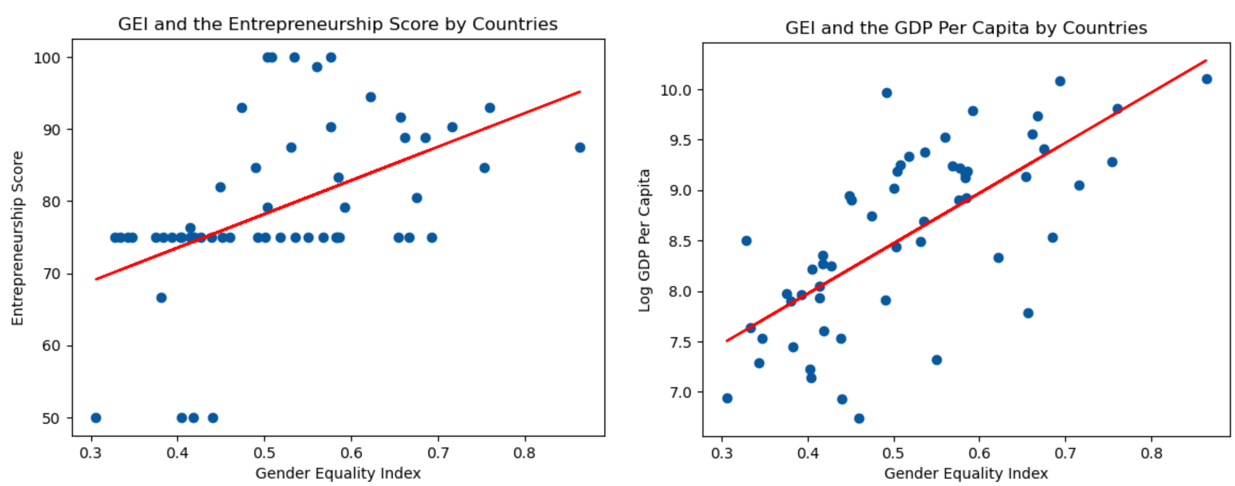


**Figure 20:** Relationships between the Entrepreneurship Score, GDP per Capita, and the GEI. Left: $R^2 = 0.246$, Right: $R^2 = 0.490$

Because of the number of related country indicators in the DCA dataset, we plotted and checked correlations between each indicator. There are strong correlations between these indicators, so we did not use these indicators in tandem with each other in our regression models. Otherwise, when creating dummy variables, we dropped 1 column to avoid multicollinearity. To informally check for issues, we monitored the

Python package “statsmodels” for multicollinearity warnings for our regressions.

## A.4 Jupyter Notebook Source Code

The source code will be available here: `https://github.com/yunfeikevinwang`. There are more in-depth explanations of the Tree algorithms we used, the process of developing our analysis framework, larger regression models, non-converted regression models, data cleaning, API web scraping, and more.

## A.5 Attempts at Proving Causality

### A.5.1 Difference in Difference

One avenue for exploring this issue is to ask the question: how do business laws protecting women against discrimination affect loan outcomes for women owned businesses? We will use the Entrepreneurship Score as a proxy for these laws (recall this is the definition of the Entrepreneurship Score), and see how a change in this score affects loan outcomes.

Our setup will be as follows: Control Group: Countries in which the Entrepreneurship Score did not change during the duration of the DCA loan program in which we have women owned data (2008-2015) Treatment Group: Countries in which the Entrepreneurship Score increased by 25 pts in 2008-2015.

The treatment we define as an increase of 25 pts in the Entrepreneurship Score, meaning one new law was passed to protect women against discrimination as measured by this indicator.

We identified 2 potential experimental groups that satisfy these requirements. Group 1: Cambodia, Albania, North Macedonia Entrepreneurship Scores increased 25 pts in 2010. Group 2: Mexico, Nicaragua Entrepreneurship Scores increased 25 pts in 2014. Our control group will be the majority of other countries in the DCA dataset, not included in these groups, in which the score did not change. Unfortunately, this did not yield statistically significant results, which are detailed in the source code (See A.4).

### A.5.2 Instrumental Variables

A more ambitious goal would be to find some instrument for the relationship between Is Woman Owned? (call $X$) and the Loan Size variables (call $Y$). One proposal would be to use the Entrepreneurship Score (call $I$) as our instrument. However, this breaks down very quickly.

What works: 1. We have shown $X$ has a negative correlation with $Y$. We want to prove $X$ causes a negative effect on $Y$. 2. Presumably, $I$ should have positive causal effect on $Y$. Better laws for women means more women owned businesses. However, this needs to be proved using our data.

What doesn't work: 3. Exclusion Restriction: While it may seem that $I$ should have no direct relationship with $Y$ (i.e. how can laws for women affect overall loan size), there are many confounding factors that $I$ can be related to. For example, places with a higher $I$ may have better institutions/economy, so naturally have higher $Y$. 4. $I$ is not randomly assigned. While women cannot choose the country they are born in, they can move/lobby for better laws, meaning they have some influence on $I$. Thus, even if we find $I$ correlates $Y$ positively, we cannot conclude causality since we do not have randomly assigned $I$.

Thus Instrumental Variables are not a viable strategy for proving causation using the instrument we discussed above.

### A.6 Basic Regression Tree

We will briefly explain the mathematical setup behind tree algorithms for those unfamiliar.
Let $R$ be a rectangular containing our independent variables $X_1, X_2, ..., X_n$.
Split $R$ into two regions $R_1 = \{(x_1, ..., x_n) \in R : x_i \leq s\}$ and $R_1^c = \{(x_1, ..., x_n) \in R : x_i > s\}$ and by solving our objective function:

$$\min_{i,s} \left[ \sum_{\mathbf{x}_k \in R_1} (y_k - \hat{y}_{R_1})^2 + \sum_{\mathbf{x}_k \in R_1^c} (y_i - \hat{y}_{R_1^c})^2 \right]$$

where the estimators $\hat{y}_{R_1}, \hat{y}_{R_1^c}$ are the sample means of $y$ over the regions $R_1$ and $R_1^c$ respectively.

Intuitively, we are deciding on $i$, which variable to split on, and $s$ how to split on this variable, to minimize our RSS. Then, we recursively split each region $R_1, R_1^c$ using this same procedure, until we reach some stopping condition. This condition can be when the number of total resulting regions has reached/exceeded a certain number. All flavours of trees fundamentally follow this overall procedure with different tweaks. For details on more sophisticated algorithms such as random forests, using bootstrapping techniques and cross-validation to address over-fitting, see A.4.