The Gender Credit Gap: Using Data Analytics to Examine Financial Barriers and Their Impact on Women's Entrepreneurial Participation and Business Growth

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Abstract

A common finding is that women set up and run businesses in all economies but face a lack of access to finance. This paper aims to identify where the gender gap in credit comes from, why it persists and how to utilise data analytics to accurately measure it. A systematic review of peer reviewed academic publications from 2016 to 2025 has been undertaken to understand where the gap in credit is occurring. It seems that there is a gap in terms of discouragement, more difficult lending requirements, biased questioning and lack of finance. This leads to negative implications for capital allocation and business growth for women. A method has also been developed those lenders, regulators and researcher can use in the field of algorithmic credit. This paper is a review paper. The tables contain data from previous academic papers.

Keywords: *Gender Credit Gap; Women Entrepreneurs; Access to Finance; Credit Discrimination; Data Analytics; Venture Capital; MSMEs*

1. Introduction

If you ask any female founder about barriers, they will tell you how difficult it was to get funding. Usually a direct no isn't given, instead females may face barriers such as having to include a guarantor clause that their male counterparts wouldn't have to, being questioned extensively instead of pitched to, or not applying because they know they won't get the answer they want. These barriers are not visible in a table unless you know where to look. Using data analytics can help. Now banks, development organizations and fintech companies have accurate data on applications, approvals, interest rates and repayments. If used correctly this can help identify if there is a gap in credit and where it occurs. However, if not used correctly it can mask the issue using averages or automate the process.

This paper aims to provide a structure to the recent findings in literature surrounding the gender credit gap. Specifically, this paper will answer the following questions:

Where in the funding process do female entrepreneurs face discrimination?

What evidence do we have regarding participation and growth?

How can we measure the gap and what should analysts be aware of?

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2. Conceptual Background

To understand the gender credit gap it is best viewed as a collection of differences. The basic definition is the difference between the likelihood, amount or cost of external finance received by women owned/led businesses and otherwise similar male owned businesses. The phrase "otherwise similar" holds the most weight. On average women run smaller, younger businesses in different sectors meaning direct comparisons can be misleading. Reputable work will compare similar businesses or use experiments to only change the applicant's gender.

Generally, economists will identify three mechanisms. Taste based discrimination occurs when lenders/investors prefer working with one group. Statistical discrimination occurs when decision makers use gender as an indicator of unknown risk factors. Self-selection occurs as women will not apply or ask for as much due to anticipated bias. These can overlap meaning different solutions are needed. Using data analytics can help identify the story behind the data.

In debt markets there is an incentive to have collateral and a history meaning many women will not have this due to unequal asset ownership. In equity markets there is an emphasis on networks and personal judgment meaning there is more opportunity for bias.

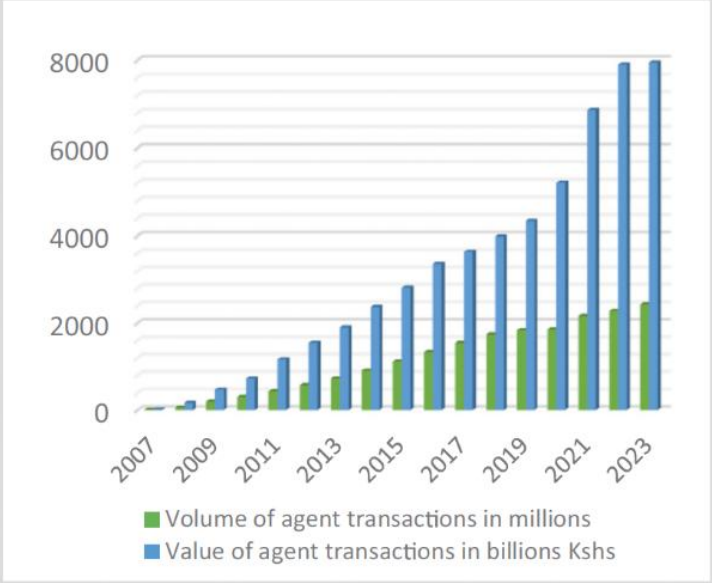


Figure 1: This figure shows mobile money agents.

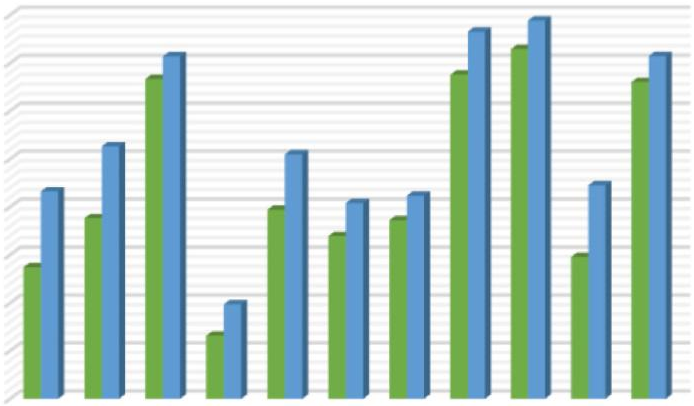


Fig 2: The figure shows mobile money usage

3. Method

We followed a structured evidence synthesis. We searched for peer-reviewed articles on gender, credit, entrepreneurship finance and algorithmic lending, restricted to 2016–2026, and kept studies that met four tests: a clear empirical design, a well-defined financial outcome, a gender comparison, and a verifiable digital object identifier.

Twelve studies form the core evidence base (Table 1). We extracted the setting, the data and method, and the central finding, then grouped results by mechanism. We did not run new statistical analyses, and we report only quantities that appear in the cited papers.

Table 1. Core evidence base

Study	Setting	Data and method	Central finding
Ongena & Popov (2016)	17 European countries	Survey of roughly 6,000 small firms; cultural gender-bias proxy	Women opt out of applying in high-bias countries, though banks do not discriminate against those who apply
Beck et al. (2018)	Albania, one lender	Loan-level data; quasi-random officer assignment	Opposite-sex pairs lead to lower repeat borrowing and tougher terms, with no higher arrears
Brock & De Haas (2023)	Turkey	Lab-in-the-field with 334 loan officers	Equal approval rates, but 26% higher odds of a guarantor requirement for women
Chaudhuri et al. (2020)	India	National MSME dataset	Women-owned firms disadvantaged in institutional credit
Morazzoni & Sy (2022)	United States	Kauffman firm data; calibrated model	Women face more rejections; closing the gap lifts output by 4%
Ewens & Townsend (2020)	United States	AngelList platform data	Male investors show less interest in women-led startups
Kanze et al. (2018)	United States	Field study plus experiment	Women get "prevention" questions and raise less capital

Study	Setting	Data and method	Central finding
Brush et al. (2018)	United States	All VC-funded firms, 2011–2013	Women-led firms receive a very small share of VC dollars
Poczter & Shapsis (2018)	United States	Televised pitch competition	Similar success rates, smaller amounts for women
Balachandra (2020)	United States	Synthesis of VC decision studies	Male-dominated VC firms help explain the funding gap
Bellucci et al. (2025)	Global angel market	Business angel deal data, 2018–2020	Gender of investor and investee both matter for funding
Fuster et al. (2022)	United States	Mortgage data; machine learning	Algorithmic gains are unevenly shared across groups

4. Findings: Where the Gap Appears

4.1 Before the application: discouragement

The first surprise in the literature is how much of the gap opens before a lender ever sees a file. Ongena and Popov (2016) linked survey data on about 6,000 small businesses in 17 countries to a measure of cultural gender bias. In high-bias countries, female entrepreneurs were more likely to skip the formal application and lean on informal finance, even though banks did not appear to discriminate against women who did apply. The authors read this as anticipation: if you expect to be turned away, you stay away. A lender studying only approved and rejected files could look perfectly fair while losing would-be borrowers upstream.

Women's own funding requests tell a similar story in equity markets. Poczter and Shapsis (2018), studying a televised pitch competition, found that success rates were similar for male and female teams, yet the amounts differed, partly because women asked for less capital.

4.2 Inside the lender: conditions rather than refusals

When women do apply, bias tends to hide in the terms. Brock and De Haas (2023) gave 334 Turkish loan officers the same small-business applications and randomized only the applicant's gender. Approval rates were the same for men and women. Yet officers were 26% more likely to make approval conditional on a guarantor when the applicant was presented as a woman, and the effect was concentrated among young, inexperienced and gender-biased officers. It was also strongest for women in male-dominated industries, a pattern that helps keep entrepreneurship segregated by sector.

Beck, Behr and Madestam (2018) found something related in Albania. First-time borrowers assigned to officers of the opposite sex were less likely to return for a second loan and paid higher interest rates, around 38 basis points more, on smaller and shorter loans, with no sign of worse repayment. The bias weakened as officers gained exposure to the other gender and where competition among lenders was stronger.

Both studies share a lesson. An approval-rate comparison, the first thing most dashboards would show, would have found nothing in either setting. The disadvantage lives in pricing, collateral, loan size and the decision to come back.

4.3 Equity finance: questions, networks and who sits at the table

Equity markets show larger and more visible gaps. Brush et al. (2018) examined US venture-backed firms from 2011 to 2013 and reported that all-male teams were four times as likely to receive venture funding as teams with even one woman, and that 97% of venture dollars went to companies with a male CEO. Balachandra (2020) argues that the gender makeup of the investors matters, noting that about 93% of venture capitalists are men.

Two studies get closer to mechanisms. Ewens and Townsend (2020), using AngelList data, found that male investors expressed less interest in women-led startups than in observably similar male-led ones, while female investors showed more. Importantly, the male-led startups that male investors backed did not outperform the female-led ones they backed, which is hard to square with a purely financial explanation. Kanze et al. (2018) analysed investor questions at a major startup competition and found that men were asked promotion-focused questions about growth and gains, while women were asked prevention-focused questions about risk and losses. In their experiment, ventures answering promotion questions attracted roughly twice the funding of those answering prevention questions. Bellucci et al. (2025) extend the picture to business angels worldwide, examining both the supply and demand sides of early-stage equity.

4.4 Small firms in emerging markets

The pattern is not limited to rich countries. Chaudhuri, Sasidharan and Raj (2020), using a comprehensive dataset of Indian micro, small and medium enterprises, found that women-owned firms were disadvantaged in access to institutional credit, and they argued that tackling discrimination could narrow the performance gap between male- and female-owned firms.

Table 2. Mechanisms, evidence and the signals analysts can track

Mechanism	Illustrative evidence	Observable signal
Self-selection and discouragement	Ongena & Popov (2016); Poczter & Shapsis (2018)	Share of firms that needed credit but did not apply; ask size by gender
Conditional approval	Brock & De Haas (2023)	Guarantor or collateral requirements, holding the application constant
Pricing and loan structure	Beck et al. (2018)	Interest rate, amount and maturity, controlling for arrears
Investor bias in evaluation	Ewens & Townsend (2020); Kanze et al. (2018)	Interest rates by investor gender; type of questions asked
Network and gatekeeper effects	Brush et al. (2018); Balachandra (2020)	Funding share by founder-team composition; investor gender mix

5. Consequences for Participation and Growth

Why should anyone beyond the entrepreneurs themselves care? Because a credit gap that is not explained by risk wastes productive capital. Morazzoni and Sy (2022) offer the clearest quantification. Using US data from the Kauffman Foundation, they found that female entrepreneurs were more likely to be rejected for loans and had a higher average product of capital, which is a sign that their firms were starved of funds they could have used well. In a calibrated model, removing the credit imbalance raised output by about 4% and reduced capital misallocation by 12%. The same paper notes that women received only 2.2% of total US start-up funding in 2018.

Participation effects follow naturally. When women expect rejection, as Ongena and Popov (2016) document, fewer of them seek formal finance, and some never start the business at all. Those who do start often begin smaller and stay smaller. Brock and De Haas (2023) show how guarantor rules can fall hardest on women in male-dominated sectors, which discourages entry into exactly the industries where gender representation is lowest. In India, Chaudhuri et al. (2020) tie weaker credit access to a performance gap between male- and female-owned small firms.

Causation deserves care: most of these studies identify disadvantage in access rather than a clean effect on revenue growth, which also depends on management, networks and household constraints. Still, the pattern is consistent across settings.

6. A Data Analytics Framework for Measuring the Gap

6.1 Build the funnel, not just the outcome

The studies above suggest a simple rule: measure the whole journey. A credible gender-credit analysis should track four stages: the need for finance, the decision to apply, the lender's response and terms, and the firm's subsequent performance. Survey data such as enterprise or household surveys can estimate need and discouragement. Administrative loan data capture applications, terms and repayment.

6.2 Compare like with like, and use designs that isolate gender

Raw averages are misleading because firms differ. Analysts can use regression with rich controls, matching, or decomposition methods that split a gap into the part explained by observable characteristics and the part left over. Experiments are stronger still. The Turkish lab-in-the-field design randomised applicant gender on identical files, and Beck et al. exploited as-good-as-random assignment of borrowers to officers. Brock and De Haas also applied a causal forest algorithm to find which officers were responsible, which illustrates how machine learning can serve fairness analysis and not only prediction.

6.3 Treat algorithms as part of the problem and the solution

Credit scoring is increasingly automated, and the evidence on fairness is mixed. Fuster et al. (2022), studying US mortgages, found that machine learning predicted default better than a traditional model, yet the gains were not shared equally, and some minority borrowers were less likely to benefit. Their analysis concerns race and ethnicity rather than gender, but the lesson carries over: a more accurate model can still widen disparities between groups. Lenders should therefore test every model for differences in approval, pricing and error rates by gender, and should look hard at proxy variables such as sector, collateral type or phone usage that may stand in for gender. Algorithms have one real advantage, however. They remove the officer-level variation documented by Beck et al. and Brock and De Haas, so a well-audited model may be fairer than a discretionary human process.

Table 3. A practical analytics pipeline for gender credit analysis

Stage	Data needed	Technique	Output
Need and discouragement	Enterprise or household survey	Descriptive analysis; logit of non-application	Discouraged-borrower rate by gender
Application and approval	Loan applications, decisions	Matching; regression; decomposition	Adjusted approval gap
Terms and conditions	Rates, amounts, maturities, guarantor flags	Fixed-effects models; audit tests	Pricing and collateral gap

Stage	Data needed	Technique	Output
Bias diagnostics	Officer and branch identifiers	Causal forest; heterogeneity analysis	Where and by whom disparity arises
Model fairness	Scoring model outputs	Group error-rate and calibration tests	Fairness report before deployment
Business outcomes	Repayment and firm performance records	Event-study; survival analysis	Growth and default by gender

6.4 Pitfalls worth naming

Four traps recur. Analysing only funded firms hides people who never applied. Small samples of women-led firms can make real gaps look insignificant. Comparing default rates ignores the higher bar women may have cleared to get approved. And pooling sectors can hide concentrated disadvantage, as the Turkish evidence shows.

7. Conclusion

The gender credit gap is real, but it rarely looks the way people expect. It shows up as discouragement before the application, as guarantors and pricing during it, and as biased questions and thinner networks in equity markets. These frictions waste capital that women-led firms could use productively.

Data analytics is both a spotlight and a risk. Used with careful designs, funnel-wide data and fairness testing, it can make hidden disadvantage visible and help institutions correct it. Used naively, it will report equal approval rates and declare the matter closed. The most useful next step is not another headline statistic but better linked data, routine reporting of terms and discouragement by gender, and a willingness to look past the first number a dashboard shows.

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