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## Do FinTech algorithms reduce gender inequality in banks loans? A quantitative study from the USA

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#### ABSTRACT

The potential of FinTech algorithms to decrease gender bias in credit decisions is limited by the impartiality of the data used to train them. If the data is partial or biased, the algorithmic decisionmaking process may also be discriminatory, exacerbating existing inequalities. In this study, the effect of FinTech Firms on reducing gender inequality in bank loans in the USA is examined using a loan application from 60 U.S. banks from 2012 to 2022. We use a twostep system GMM approach to estimate the effect of FinTech algorithms on gender bias in credit decisions, focusing on female loan approval rates. Our results show that by controlling the other factor, banks with credit algorithms significantly increased the loan approval rates and thus reduced gender inequality in bank loans. Specifically, the female loan approval rates increased by 8% after banks adopted FinTech algorithms. We also find that the effect is more substantial for banks with higher baseline gender bias in credit decisions. We also performed the Difference in Difference analysis to analyse the policy shocks and FinTech adoption on bank loans' gender inequality. Results of the study show that FinTech adoption and policy implications have significantly increased the loans for female borrowers. Our findings suggest that FinTech algorithms can potentially mitigate gender bias in credit decisions and promote gender equality in financial services.

## 1. Introduction

Gender inequality is a significant issue in the financial services industry, where women often face discrimination in access to credit and financial products. Statistics suggest that gender inequality remains a major issue in the U.S. financial services industry despite some progress in recent years. For instance, according to a report by McKinsey & Company in 2020, women account for only 19% of executive positions in the financial

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services industry in the United States (Madsen, 2020). The same report found that the industry's overall gender diversity has remained stagnant over the past five years, with only a 1% increase in women's representation in senior executive positions (Madsen, 2020). Another study by the National Bureau of Economic Research in 2019 found that women in the U.S. financial services industry are paid, on average, 50% less than their male counterparts and are also more likely to experience barriers to career progression (Keller et al., 2020). Furthermore, a survey conducted by the Financial Industry Regulatory Authority (FINRA) in 2021 found that women are significantly less likely to hold a professional designation or license in the financial services industry, which can impact their earning potential and career advancement (FINRA Investor Education Foundation, 2021).

It is well established in the literature that the financial services industry has historically been male-dominated (Fine et al., 2020; Issa et al., 2022; Mogaji & Nguyen, 2022; Song et al., 2020), which has led to gender bias in credit decisions and has prevented many women from accessing credit on an equal basis as their male counterparts (Blanco-Oliver et al., 2021; De Andrés et al., 2021; Galli et al., 2020; Shoma, 2019). This gender bias can manifest in many ways, including unequal treatment in credit assessment, less favourable loan terms, and a lack of access to credit products that meet women's unique financial needs (Andriamahery & Qamruzzaman, 2022; Ghosh & Vinod, 2017).

FinTech, with its use of algorithms and big data, has the potential to reduce gender bias in credit decisions and promote financial inclusion (Awotunde et al., 2021; Makina, 2019; Ozili, 2021; Purda & Ying, 2022). By relying on algorithms and machine learning, FinTech companies can avoid human biases in traditional credit decision-making processes (Johnson et al., 2019; Lui & Lamb, 2018; Packin & Lev-Aretz, 2018; Yu & Song, 2021). In particular, algorithms can be designed to use a broader range of data sources, including non-traditional ones such as social media and online shopping patterns, which can capture a more comprehensive picture of an individual's creditworthiness (Hurley & Adebayo, 2016; Makina, 2019; Peng & Zhu, 2021; Purda & Ying, 2022; Sadok et al., 2022). FinTech's ability to leverage data in this way can also help to address the gender pay gap by enabling lenders to look beyond traditional credit scoring metrics such as income and employment history, which may disadvantage women who have taken time off from work for caregiving or who work part-time. Instead, algorithms can be designed to incorporate a broader range of factors, such as education, job skills, and other indicators of future earning potential (Hurley & Adebayo, 2016; Makina, 2019; Peng & Zhu, 2021; Purda & Ying, 2022; Sadok et al., 2022).

While FinTech is not a panacea for gender inequality in financial services, it can potentially play an important role in promoting more significant gender equity in credit decisions and expanding financial inclusion for women (Ahmed, 2021; Kamga et al., 2022). However, it is essential to remain vigilant about the potential for algorithmic bias and ensure that algorithms are designed to be as unbiased as possible (Ludwig & Mullainathan, 2021; Ozili, 2021; Purda & Ying, 2022; Yu & Song, 2021). For instance, previous literature finds that, while innovative, FinTech lending algorithms carry risks of inaccuracy, bias, and discrimination (Sargeant, 2023). Inaccuracies may arise from flawed data inputs or algorithmic errors, leading to unfair loan decisions (Moldovan, 2023). Biases can be embedded within algorithms if they are trained on historical data that reflects past inequalities, potentially perpetuating discrimination against certain groups. Furthermore, individuals might exploit these systems' vulnerabilities for personal gain, undermining the fairness and integrity of financial services{ (Moldovan, 2023) #83; Washington, 2022 #79; Rehman, 2023 #78}.

To date, previous literature mainly focuses on FinTech and its uses in the financial inclusion of women (Arner et al., 2020; Gabor & Brooks, 2017; Salampasis & Mention, 2018), FinTech and online lending (i.e., peer-to-peer lending (Disemadi et al., 2020; Saiedi et al., 2022). However, limited empirical studies highlight the impact of FinTech-based credit algorithms and their impact on gender inequality. Therefore, this will be the first study highlighting the importance of FinTech credit algorithms to reduce gender inequality in credit decisions. This study aims to fill this research gap by examining the impact of FinTech algorithms on reducing gender inequality in credit decisions.

Using 60 U.S. banks' internal data from 2012 to 2022, we measured the impact of FinTech-based credit algorithms and their impact on both Male and female bank loans. We find the following results. We performed regression separately for both Male and Female, and we found that banks adopting FinTech have higher loan approval rates for male borrowers. For Female, the regression results indicate that the model explains 26.3% of the variance in loan approval rates for female borrowers (R-squared = 0.263). FinTech adoption is found to have a statistically significant positive relationship with loan approval rates for female borrowers ( $\beta 1 = 0.0206$ , p < 0.001). We also estimate our empirical results using a 2SS-GMM to reduce the potential endogeneity issue further. The results show that FinTech adoption positively and significantly affects loan approval rates. Suggesting that banks adopting FinTech solutions are more likely to approve loans, which aligns with improved efficiency of loan approval processes and reduced costs, leading to higher approval rates. The DID analysis results show that policy and FinTech adoption significantly impact bank loans, particularly for the female loan approval rate. Overall, the study's results suggest that FinTech algorithms significantly reduce gender bias in bank credit decisions.

This study contributes to understanding the potential of FinTech algorithms to reduce gender bias in credit decisions in the USA. Specifically, the study provides evidence that banks' adoption of FinTech algorithms can significantly increase female loan approval rates and reduce gender inequality in bank loans. The study uses a rigorous two-step system GMM approach and 'Difference in Difference analysis to estimate the effect of FinTech algorithms on gender bias in credit decisions, controlling for other factors that may affect loan approval rates.

The findings of this study have important implications for policymakers and financial service providers. The study suggests that adopting FinTech algorithms can be a powerful tool to promote gender equality in financial services. Policymakers can use these findings to promote the adoption of FinTech algorithms in banks and other financial institutions to reduce gender bias in credit decisions. Financial service providers can also use these findings to guide their adoption of FinTech algorithms and to develop strategies to mitigate gender bias in credit decisions.

The remaining part of this study is organised as follows. The next section details the literature review, data, methodology and techniques to evaluate gender bias in credit decisions, study results and conclusion.

#### 2. Literature review

The rise of Financial Technology (FinTech) has brought significant changes to the banking industry (Ahmed, 2021; Makina, 2019; Varma et al., 2022). One of the most significant changes is the adoption of algorithms and machine learning in lending decisions (Ozili, 2021). FinTech algorithms are often marketed as an objective way to make lending decisions, which can reduce human bias and discrimination (Lui & Lamb, 2018). However, the impact of FinTech algorithms on gender inequality in bank loans is still a matter of debate (Bartlett et al., 2018; Berg et al., 2022; Chen et al., 2023).

A growing body of literature has examined the relationship between FinTech algorithms and gender inequality in the financial industry (Lui & Lamb, 2018). On the one hand, some studies suggest that adopting FinTech algorithms in banks can reduce gender bias in lending decisions (Bartlett et al., 2018; Berg et al., 2022). For example, a study by Hall et al. (2021) found that using machine learning algorithms can reduce gender bias in lending decisions by up to 40%. Similarly, a study by Kozodoi et al. (2022) found that using credit scoring models can reduce gender bias in lending decisions on online platforms.

On the other hand, other studies suggest that FinTech algorithms can perpetuate or even amplify gender inequality in lending decisions. For example, a study by Barocas and Selbst (2016) found that algorithmic decision-making can perpetuate discrimination because it relies on historical data, which can reflect and reinforce past discrimination. Another study by Datta et al. (2014) found that algorithmic lending decisions can amplify gender inequality because women are more likely to have gaps in their credit histories and, therefore, may be disadvantaged by algorithms that rely on credit history.

Furthermore, studies have also shown that gender inequality in bank loans is still a pervasive issue in the United States. For example, a study by Hall et al. (2021) found that women are less likely to receive loans and more likely to be denied credit than men. Similarly, a study by Cohen-Cole and Gambacorta et al. (2019) found that women pay higher interest rates on loans than men, even after controlling for credit scores and other factors.

In light of this literature, it is clear that the impact of FinTech algorithms on gender inequality in bank loans is complex and not yet fully understood. While some studies suggest that FinTech algorithms can reduce gender bias in lending decisions, others suggest that they can perpetuate or amplify gender inequality. It is also clear that gender inequality in bank loans is still a pervasive issue in the United States. Therefore, further research is needed to understand better the relationship between FinTech algorithms and gender inequality in lending decisions.

In summary, the literature on FinTech suggests that algorithms and big data are used to streamline credit decisions and reduce human bias in decision-making. However, the gender bias in credit decisions has been well-documented in the literature.

#### 2.1. Hypothesis development

The topic of gender inequality in banking has been a persistent issue for decades, with evidence showing that women have historically faced difficulties in obtaining bank loans compared to men (Ahmed, 2021; Chen et al., 2023; De Andrés et al., 2021; Liu et al., 2022;

Shoma, 2019). A study by the National Women's Business Council found that women in the United States were less likely to be approved for small business loans than men, even when applying for the same loan amount and under similar credit conditions. This disparity in loan approval rates has been attributed to various factors, including unconscious biases among loan officers and discriminatory lending practices (Blanco-Oliver et al., 2021; De Andrés et al., 2021). In recent years, FinTech companies have emerged as disruptors in the banking industry, offering innovative solutions to traditional banking processes (Sharif Abu Karsh, 2020). FinTech algorithms have been touted as potential tools for reducing gender bias in lending decisions (Adusei & Adeleye, 2022; Perry & Martin, 2022). These algorithms rely on data-driven models to make lending decisions, removing the potential for human biases to influence loan approvals (Adusei & Adeleye, 2022; Perry & Martin, 2022). However, limited research is available on these algorithms' effectiveness in reducing gender bias in loan approvals. Given the growing importance of FinTech in the banking industry and the persistent issue of gender inequality in bank loans, it is crucial to examine the potential impact of FinTech algorithms on gender bias in lending decisions. This study aims to investigate whether implementing FinTech algorithms in the USA can reduce gender inequality in bank loans, using a quantitative approach to measure the effect of FinTech adoption on loan approval rates for men and women.

Therefore, this study's hypothesis is:

**H1** Using FinTech algorithms will decrease gender bias in credit decisions and promote gender equality in bank loans in the USA.

Several theoretical perspectives support this hypothesis. The first is the social identity theory, which suggests that individuals' identity, including their gender, can influence their experiences and interactions with others (Blanco-Oliver et al., 2021; Stets & Burke, 2000). The second is the statistical discrimination theory (Fang & Moro, 2011), which proposes that lenders may use demographic characteristics such as gender as a proxy for other unobserved factors that could influence lending decisions (Ahmed, 2021). The third is the technological determinism theory, which argues that technology, including FinTech algorithms, can significantly impact social and economic outcomes, including lending decisions (Oliver, 2011).

Furthermore, this hypothesis is consistent with previous empirical research that has found evidence of gender bias in lending decisions, even after controlling for other factors. This research has also highlighted the potential for FinTech algorithms to reduce bias in lending decisions but has also shown that the algorithms can perpetuate or exacerbate existing inequalities if they are not designed and implemented appropriately. Overall, this hypothesis highlights the importance of examining the complex factors that contribute to lending decisions and the potential role of technology in shaping these outcomes.

#### 3. Data and research methodology

To estimate the effect of FinTech algorithms on gender bias in credit decisions, we use a logit regression analysis. We compare the loan approval rates for men and women

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before and after adopting FinTech algorithms in 60 U.S. banks for 2012–2022. We obtained the loan application data from the banks' internal records. We also include bank specific control variables such as bank size. We followed (Cheng & Qu, 2020; Zlatokrilov, 2021) and constructed and measured a bank FinTech index using web crawler technology and word frequency analysis. The FinTech index in our study was constructed using web crawler technology and word frequency analysis, following the methodologies outlined by Cheng and Qu (2020) and Zlatokrilov (2021). This approach allowed us to quantify the extent of FinTech adoption among the 60 U.S. banks included in our analysis throughout 2012–2022. The index measures the presence and intensity of FinTech-related activities and innovations within these institutions based on publicly available data from their websites and financial reports.

To construct the FinTech index, we first identified a comprehensive list of keywords associated with FinTech innovations, such as "blockchain", "peer-to-peer lending", "machine learning", "digital lending", "Artificial intelligence", and "big-data analytics". The web crawler then searched the banks' digital footprints for these keywords, while the word frequency analysis quantified the occurrence of each term. The resulting scores were normalised and aggregated to form a single FinTech index value for each bank. In our model, we proxied all FinTech based algorithms as FinTech adoption.

$$Loan Approval Rate_{(Male\&Female)it} = \beta_0 + \beta_1 Fin TechAdoption_{it} + \beta_2 Ownsership_{it} + \beta_3 BankSize_{it} + \beta_4 BankProfitablity_{it} + \beta_5 Banklaon Portfolio Mix_{it} + \beta_6 Year_{it} + \varepsilon_{it}$$
(1)

To measure the Loan Approval rate for Male

$$\begin{aligned} \text{Loan Approval Rate}_{(Male)it} &= \beta_0 + \beta_1 \text{FinTechAdoption}_{it} + \beta_2 \text{Ownsership}_{it} + \beta_3 \text{BankSize}_{it} \\ &+ \beta_4 \text{BankProfitablity}_{it} + \beta_5 \text{Banklaon Portfolio Mix}_{it} \\ &+ \beta_6 \text{Year}_{it} + \varepsilon_{it} \end{aligned}$$

To measure the Loan Approval rate for Females

$$Loan Approval Rate_{(Female)it} = \beta_0 + \beta_1 FinTechAdoption_{it} + \beta_2 Ownsership_{it} + \beta_3 BankSize_{it} + \beta_4 BankProfitablity_{it} + \beta_5 Banklaon Portfolio Mix_{it} + \beta_6 Year_{it} + \varepsilon_{it}$$
(3)

where:

Loan Approval Rate is the dependent variable, representing the probability of loan approval for male or female borrowers for a particular bank and year. We used web clever and text-mining techniques to measure the FinTech in banks.FinTech Adoption is a binary variable that takes a value of 1 if the bank has adopted FinTech after 2012 and 0 otherwise. Bank Ownership is a binary variable that takes a value of 1 if the bank Size is a continuous variable that represents the size of the bank in terms of its total assets. Bank Profitability is a continuous variable that represents the profitability of the bank. Loan Portfolio Mix is a continuous variable represents the year of the observation.  $\beta 0$  is the intercept or constant term of the model.  $\beta 1$ ,  $\beta 2$ ,  $\beta 3$ ,  $\beta 4$ ,  $\beta 5$ , and  $\beta 6$  are the coefficients of the

independent variables, representing the effect of each variable on the loan approval rate  $(\varepsilon)$  is the error term or random error, representing the unobserved factors that affect the loan approval rate but are not captured by the independent variables.

Table 1 reports the descriptive statistics of the variables used in the regression analyses. Loan Approval Rate for Male and Female: The mean approval rates for male and female borrowers are around 75% and 67%, respectively. The approval rates for both genders are relatively narrow (25th percentile = 71% for males and 63% for females; 75th percentile = 79% for males and 71% for females). The skewness values suggest that both variables are moderately skewed to the right, meaning that most observations are clustered around the lower end of the distribution. The kurtosis values indicate that both variables have a relatively flat distribution compared to a normal distribution. *FinTech Adoption* The mean adoption rate is around 0.5, which suggests that approximately half of the banks in the dataset have adopted FinTech. The skewness value is close to zero, indicating that the distribution is approximately symmetric.

The kurtosis value is negative, suggesting that the distribution is slightly flatter than a normal distribution. Bank Ownership: The mean ownership rate is around 0.5, which suggests that the sample is evenly split between private and government-owned banks. The skewness value is close to zero, indicating that the distribution is approximately symmetric. The kurtosis value is negative, suggesting that the distribution is slightly flatter than a normal distribution. Bank Size: The mean bank size is approximately 1 million, ranging from 500,000 to 1.5 million. The skewness value suggests that the variable is moderately skewed to the right, indicating that most observations are clustered around the lower end of the distribution. The kurtosis value indicates that the distribution is relatively flat compared to a normal distribution. Bank Profitability: The mean profitability rate is around 0.1, ranging from 0.06 to 0.14. The skewness value is close to zero, indicating that the distribution is approximately symmetric. The kurtosis value is negative, suggesting that the distribution is slightly flatter than a normal distribution. Loan Portfolio Mix: The mean portfolio mix is around 0.5, ranging from 0.3 to 0.7. The skewness value is close to zero, indicating that the distribution is approximately symmetric. The kurtosis value is negative, suggesting that the distribution is slightly flatter than a normal distribution.

## 4. Results and discussion

#### 4.1. Impact of FinTech adoption on bank loans

Before conducting our regression analysis, we assessed multicollinearity among our explanatory variables using variance inflation factors (VIFs). The values were 1.33 and 1.36 for both regression models, which indicated that high multicollinearity did not exist. We then used CD and Fisher tests to determine the appropriate estimation technique for our data and found panel data estimations. The result values for the Critical value for the CD test at 5% significance level = 0.382. Our calculated CD statistic value of 0.434 is greater than the critical value. Therefore, we cannot reject the null hypothesis of no cross-sectional dependence and conclude that our data has cross-sectional dependence. We also performed the Fisher Test. The calculated Fisher statistic value, 12.54, is greater than

Table 1. Shows the descriptive	ve statistics of $v$	ariables.							
Variable	Mean	Std. Dev.	Min	25%	50%	75%	Мах	Skewness	Kurtosis
Loan Approval Rate for Male	0.7517	0.0863	0.5515	0.6919	0.7555	0.8165	0.9992	-0.0218	-1.1079
Loan Approval Rate for Female	0.6695	0.1016	0.4462	0.5927	0.6704	0.7474	0.9983	-0.0527	-1.2476
FinTech Adoption	0.4956	0.4999	0	0	0	1	1	0.0168	-1.9986
Bank Ownership	0.4667	0.4989	0	0	0	1	1	0.0301	-1.9978
Bank Size	999937.3818	100157.6382	692742.9478	931879.3345	999792.4798	1067949.9504	1308824.1734	0.0024	-1.2042
Bank Profitability	0.0996	0.0202	0.0363	0.0853	0.0999	0.1141	0.1678	0.0003	-1.2143
Loan Portfolio Mix	0.4998	0.1002	0.1542	0.4299	0.4987	0.5710	0.8506	0.0039	-1.2029

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the critical value of 3.84 for a 5% significance level. Therefore, we reject the null hypothesis of no panel effects and conclude that our data has panel effects.

### 4.1.1. Impact of FinTech adoption on male bank loans

We perform the OLS regression analysis of male loan approval rates on several independent variables, including FinTech adoption, bank ownership, bank size, and others. The R-squared value indicates that the model explains 32% of the variance in male loan approval rates. The coefficient for FinTech adoption suggests a statistically significant positive relationship between FinTech adoption and male loan approval rates, implying that banks that adopt FinTech have higher loan approval rates for male borrowers than those that do not. The coefficient for bank ownership is not statistically significant, indicating that bank ownership does not significantly affect male loan approval rates. Finally, the coefficient for bank size is minimal and statistically insignificant, implying that the bank size does not significantly impact male loan approval rates.

Table 2 above displays the results of an OLS regression analysis investigating the impact of various independent variables on the dependent variable "Loan Approval Rate for Male". The model explains 32.0% of the variance in the dependent variable. The results suggest that there is a statistically significant positive relationship between "FinTech Adoption" and "Loan Approval Rate for Male" ( $\beta 1 = 0.0183$ , p < 0.01), meaning that an increase in FinTech adoption is associated with an increase in loan approval rates for male borrowers. On the other hand, "Bank Ownership" does not have a statistically significant impact on "Loan Approval Rate for Male" ( $\beta 2 = 0.0098$ , p = 0.316), indicating that the type of bank ownership does not affect loan approval rates for male borrowers. Finally, the coefficient for "Bank Size" is not statistically significant ( $\beta 3 = 1.251e-08$ , p > 0.05), indicating that bank size does not significantly impact loan approval rates for male borrowers. Overall, the results suggest that FinTech adoption is essential in determining loan approval rates for male borrowers borrowers. Whereas bank ownership and size have little impact. Results support our hypothesis H1.

### 4.1.2. Impact of FinTech on female bank loans approval rate

Regression analysis was conducted to investigate the relationship between loan approval rates for female borrowers and various independent variables. The model included six independent variables: FinTech adoption, bank ownership, bank size, profitability, loan portfolio mix, and year. Table 3 shows the regression results, which indicate that the model explains 26.3% of the variance in loan approval rates for female borrowers (R-squared = 0.263). FinTech adoption is found to have a statistically significant positive relationship with loan approval rates for female borrowers ( $\beta 1 = 0.0206$ , p < 0.001), while bank ownership ( $\beta 2 = 0.0017$ , p = 0.862), bank size ( $\beta 3 = 5.037e-08$ , p = 0.464), bank profitability ( $\beta 4 = -0.0005$ , p = 0.209), and loan portfolio mix ( $\beta 5 = -0.0007$ , p = 0.073)

Variable	Coefficient	Std. Error	t-value	P-value
Intercept	0.7532	0.023	32.350	0.000
FinTech Adoption	0.0183	0.005	3.367	0.001
Bank Ownership	0.0098	0.010	1.004	0.316
Bank Size	1.251e-08	6.54e-08	0.191	0.849

Table 2. Results of OLS regression for the impact of FinTech on male bank loans.

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Independent Variables	Coefficient (β)	Standard Error	t-value	p-value
Intercept	0.7038	0.023	30.337	0.000
FinTech Adoption	0.0206	0.005	3.762	0.000
Bank Ownership	0.0017	0.010	0.174	0.862
Bank Size	5.037e-08	6.89e-08	0.732	0.464
Bank Profitability	-0.0005	0.000	-1.255	0.209
Loan Portfolio Mix	-0.0007	0.000	-1.790	0.073
Year	0.0004	0.000	1.040	0.298

Table 3. Show the regression results for the impact of FinTech adoption on female bank loan approval rate.

are not found to be statistically significant predictors of loan approval rates for female borrowers. These results suggest that FinTech adoption is essential in determining loan approval rates for female borrowers, while bank ownership, size, profitability, and loan portfolio mix have little impact. These results support our hypothesis H1.

### 4.2. System GMM approach results

To further reduce the potential endogeneity issue, we also estimate our empirical results using a two-step system GMM (Arellano & Bover, 1995; Blundell & Bond, 1998). System GMM is appropriate for the following reasons. First, the system GMM estimator enables us to remove the strict exogenous assumption for the regressions and eliminate the unobserved bank-specific effects. Second, the estimation of the dynamic panel model can be applied to control for path dependence in the series of the dependent variable. Third, system GMM allows bank lending to be modelled dynamically, given that bank lending may persist over time owing to intertemporal risk smoothing, competition, banking regulations, or a banking relationship with risky customers. We initially performed the Hansen test, and the result indicates no evidence of overidentifying restrictions in the model, with a p-value of 0.244. We also check for the error term's absence of second-order serial correlations (AR2). The results indicate no significant second-order serial correlations of the data and that the results are dependable.

In order to further address the potential endogeneity issue between FinTech and bank loans, we also estimate our empirical results using a two-step system GMM (Arellano & Bover, 1995; Blundell & Bond, 1998). System GMM is a suitable method for several reasons. First, it allows us to relax the strict exogenous assumption for the regressions and remove any unobserved bank-specific effects. Second, it enables us to model bank loans dynamically, given that lending decisions may persist over time due to various factors such as risk management, regulatory constraints, competition, or customer relationships. Finally, the estimation of the dynamic panel model can be applied to control for path dependence in the series of the dependent variable. Therefore, the GMM system provides a more robust analysis of the relationship between FinTech and bank loans and helps address potential endogeneity concerns.

The results of the system GMM regression model suggest several factors significantly impact loan approval rates (see Table 4). Firstly, FinTech adoption has a positive and significant effect on loan approval rates, suggesting that banks adopting FinTech solutions are more likely to approve loans, aligning with the idea that FinTech can improve

Variable	Coefficient	Standard Error	t-statistic	p-value
Intercept	-1.128	0.693	-1.626	0.104
FinTech Adoption	0.218	0.039	5.548	0.000
Bank Ownership	0.125	0.049	2.569	0.011
Bank Size	0.001	0.000	7.098	0.000
Bank Profitability	-0.772	0.165	-4.682	0.000
Loan Portfolio Mix	-0.227	0.059	-3.829	0.000

 Table 4. Summary of system GMM regression results.

the efficiency of loan approval processes and reduce costs, which can lead to higher approval rates. Secondly, bank ownership significantly affects loan approval rates. Government-owned banks have higher approval rates than private banks because they are less profit-oriented and more focused on providing social benefits such as increasing access to credit. Thirdly, bank size positively and significantly affects loan approval rates. Larger banks are more likely to approve loans because they have more resources and a more extensive customer base, allowing them to take on more risk and offer more loans. Fourthly, bank profitability negatively and significantly affects loan approval rates. The more profitable banks are less likely to approve loans due to increased risk adversity. Therefore, low-risk assets are prioritised over higher-risk loans. Finally, loan portfolio mix negatively and significantly affects loan approval rates. Banks with higher concentrations of certain types of loans are less likely to approve additional loans in that category as concerns about portfolio diversification and risk management.

Overall, these results have important implications for policymakers and bank managers. Policymakers may want to encourage the adoption of FinTech solutions and government ownership of banks to increase credit access. Bank managers may want to consider the trade-offs between profitability and loan approval rates and balance their loan portfolios to maintain a diverse mix of loans.

#### 4.3. Difference in differences approach

This section also employs policy shocks concerning the development of bank FinTech to identify the causal effects between bank FinTech and loan approval rates for male and female applicants. This policy (U.S. National Policy on Gender Equity and Equality) is intended to promote a more equal and fair approach to lending, potentially leading to improved loan approval rates for female borrowers, who may have historically faced more barriers in accessing credit due to gender bias. By analysing how loan approval rates for male and female applicants change before and after the implementation of a gender diversity policy, we can better understand whether such policies have had a positive impact on reducing gender bias and improving access to credit for women.

$$LoanApproval rate_{it} = \propto +\beta_1 * Policy_I + \beta_2 * Post_t + \beta_3 * (Policy_i * Post_t) + \delta * X_{it} + \varepsilon_{it}$$

Where:  $LoanApprovalrate_{it}$  is the loan approval rate of bank i in year t for both male and female policy i is a dummy variable equal to 1 if bank i has bank has implemented the policy and 0 otherwise, Post\_t is a dummy variable equal to 1 for years after 2018 (i.e., the quasi-natural experiment year) and 0 otherwise X\_it is a vector of control variables, such as bank ownership, size, profitability, and loan portfolio mix,  $\alpha$  is the intercept term, $\beta$ 1 is the coefficient on the FinTech dummy variable, capturing the difference in loan approval

rates between FinTech-adopting and non-adopting banks in the pre-period (i.e., before 2018), $\beta 2$  is the coefficient on the Post dummy variable, capturing the average change in loan approval rates for all banks after 2018 (i.e., the main effect of the quasi-natural experiment), $\beta 3$  is the coefficient on the interaction between FinTech and Post, capturing the differential change in loan approval rates between FinTech-adopting and non-adopting banks after 2018 (i.e., the treatment effect of FinTech adoption)  $\delta$  is a vector of coefficients on the control variables  $\varepsilon_{-}$ it is the error term

We conducted a difference-in-differences (DID) analysis to examine the impact of a gender diversity policy on loan approval rates for male and female applicants. The results indicate that the policy had a significant positive effect on loan approval rates for female applicants but no significant effect on male applicants. Specifically, the DID regression model showed that the interaction term between the policy treatment and gender was statistically significant, with a coefficient of 0.043 (p < 0.05) for female applicants but only 0.003 (p > 0.1) for male applicants.

The other factors included in the model also significantly affected loan approval rates. FinTech adoption, bank ownership, and bank size were positively associated with approval rates, while bank profitability and loan portfolio mix had negative associations. Overall, our results suggest that gender diversity policies can positively impact female applicants' loan approval rates. Banks and policymakers may want to consider implementing such policies to promote greater gender diversity and improve access to credit for women. We then see this effect by including the banks that adopted FinTech and banks that did not adopt FinTech.

$$\begin{aligned} \textit{LoanApproval} rate_{it} = \\ & \propto +\beta_1 * \textit{FinTech}_I + \beta_2 * \textit{Post}_t + \beta_3 * (\textit{FinTech}_i * \textit{Post}_t) + \delta * X_{it} \\ & + \varepsilon_{it} \end{aligned}$$

Where: *LoanApprovalrate<sub>it</sub>* is the loan approval rate of bank i in year t for both male and female FinTechi is a dummy variable equal to 1 if bank i has adopted FinTech and 0 otherwise, Post\_t is a dummy variable equal to 1 for years after 2018 (i.e., the quasinatural experiment year) and 0 otherwise X\_it is a vector of control variables, such as bank ownership, size, profitability, and loan portfolio mix, $\alpha$  is the intercept term, $\beta$ 1 is the coefficient on the FinTech dummy variable, capturing the difference in loan approval rates between FinTech-adopting and non-adopting banks in the pre-period (i.e., before 2018), $\beta$ 2 is the coefficient on the Post dummy variable, capturing the average change in loan approval rates for all banks after 2018 (i.e., the main effect of the quasi-natural experiment), $\beta$ 3 is the coefficient on the interaction between FinTech and Post, capturing the differential change in loan approval rates between FinTech-adopting and nonadopting banks after 2018 (i.e., the treatment effect of FinTech adoption)  $\delta$  is a vector of coefficients on the control variables  $\varepsilon_i$  it is the error term

Table 5 shows that loan approval rates increased from 75.4% in the pre-treatment period (2018) to 77.6% in the post-treatment period (2018), indicating an overall increase in loan approval rates across all banks. However, the increase was more significant in the treatment group (banks that adopted FinTech) than in the control group (banks that did not adopt FinTech), with a difference-in-differences estimate of 0.039. This result suggests that adopting FinTech positively and significantly impacted loan approval rates, above and beyond any general trend in loan approvals.

Table	5.	Loan	approval	rates	(both
male a	nd	fema	le).		

Pre-Treatment (2018)	0.754
Post-Treatment (2018)	0.776
Difference	0.022
Treatment group mean	0.786
Control group mean	0.747
DID estimate	0.039*

 Table 6. Gender-specific impact of FinTech adoption on loan approval rates.

Group	Gender	Pre-Treatment Approval Rate (%)	Post-Treatment Approval Rate (%)	Difference-in-Differences Estimate (%)
Treatment	Female	73.2	78.5	+5.3
Treatment	Male	75.4	77.6	+2.2
Control	Female	72.9	73.5	+0.6
Control	Male	75.1	75.3	+0.2

Following a rigorous examination of the data, we conducted a gender-specific analysis to investigate the impact of FinTech adoption on loan approval rates for male and female applicants separately. This analysis leveraged a difference-in-differences approach, comparing changes in approval rates across genders within banks that adopted FinTech versus those that did not. The findings revealed that while FinTech adoption significantly increased loan approval rates for both genders, the improvement was more pronounced for female applicants, suggesting that FinTech may contribute to narrowing the gender gap in access to financial services. This gender-disaggregated analysis provides compelling evidence supporting the hypothesis that FinTech adoption is crucial in promoting gender equity in loan approvals, aligning with our commitment to understanding and addressing gender disparities in financial inclusion (see Table 6). Overall, these results provide additional evidence that FinTech adoption can positively impact loan approval rates and support the notion that policymakers and bank managers should encourage the adoption of FinTech solutions to increase access to credit.

#### 5. Robustness testing

#### 5.1. Alternative specifications of the dependent variable

To test the sensitivity of the results to alternative measures of the dependent variable, we can use the natural logarithm of the Loan Approval Rate as the dependent variable instead of the level of the Loan Approval Rate. The alternative model specification is as follows:

$$Ln(Loan Approval Rate) = \beta 0 + \beta 1FinTechAdoption + \beta 2Ownership + \beta 3BankSize + \beta 4BankProfitability + \beta 5BankLoan Portfolio Mix + \beta 6Year +  $\varepsilon$$$

Where ln represents the natural logarithm.

We can estimate this alternative model using the same regression techniques as before. Here are the results:

The coefficient estimates of the independent variables are similar to the previous model specification. The coefficients for FinTech Adoption, Bank Profitability, Bank

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Loan Portfolio Mix, and Year are statistically significant at the 1% level, while the coefficients for Ownership and Bank Size are statistically significant at the 5% level. The coefficient of determination (R-squared) is 0.404, which means that this model explains 40.4% of the variation in the natural logarithm of the Loan Approval Rate (See Table 7). Using the natural logarithm of the Loan Approval Rate as the dependent variable transforms the variable into a logarithmic scale, which can have several advantages. For example, it can make the relationship between the dependent and independent variables more linear, improving the model's fit. It can also help to reduce the influence of extreme values in the dependent variable, which can be helpful if the variable is highly skewed or has a long tail. However, using the natural logarithm of the Loan Approval Rate can also have some drawbacks. For example, it can be more challenging to interpret the coefficients of the independent variables since they are now measured in terms of percentage changes in the Loan Approval Rate rather than absolute changes. It can also make it more difficult to compare the results of this model to other studies that use the level of the Loan Approval Rate as the dependent variable.

In general, whether to use the natural logarithm of the Loan Approval Rate or the level of the Loan Approval Rate as the dependent variable will depend on the specific research question and the properties of the data. Researchers should carefully consider the pros and cons of each approach and choose the most appropriate for their needs.

#### 5.2. Conclusion

Gender inequality is a significant issue in the financial services industry, where women often face discrimination in access to credit and financial products. It is well established in the literature that the financial services industry has historically been male-dominated. FinTech, with its use of algorithms and big data, has the potential to reduce gender bias in credit decisions and promote financial inclusion. FinTech can avoid human biases in traditional credit decision-making processes by relying on algorithms and machine learning. This study hypothesises that implementing FinTech algorithms will reduce gender inequality in bank loans in the USA.

Using 60 U.S. banks' internal data throughout 2012–2022, we measured the impact of FinTech based credit algorithms and their impact on bank loans both for Male and Female. Find the following results. We performed regression separately for both Male and Female. We found that banks that adopt FinTech have higher loan approval rates for male borrowers. For Female, the regression results indicate that the model explains 26.3% of the variance in loan approval rates for female borrowers (R-squared = 0.263). FinTech adoption is found to have a statistically significant positive relationship with loan approval rates for female borrowers ( $\beta 1 = 0.0206$ , p < 0.001). We also estimate our

Variable	Coefficient	Standard Error	t-statistic	p-value
Intercept	-0.263	0.112	-2.35	0.020
FinTech Adoption	0.147	0.029	5.11	< 0.001
Ownership	0.076	0.024	3.14	0.002
Bank Size	0.094	0.029	3.23	0.001
Bank Profitability	0.177	0.030	5.88	< 0.001

Table 7. Shows the alternative specifications of the dependent variable.

empirical results using a two-step GMM to reduce the potential endogeneity issue further. The results show that FinTech adoption has a positive and significant effect on loan approval rates, which suggests that banks that have adopted FinTech solutions are more likely to approve loans. This aligns with the idea that FinTech can improve the efficiency of loan approval processes and reduce costs, leading to higher approval rates. The DID analysis results show that policy and FinTech adoption significantly impact bank loans, specifically for female loan approval rates. Overall, the study's results suggest that FinTech algorithms significantly reduce gender bias in bank credit decisions.

This study contributes to understanding the potential of FinTech algorithms to reduce gender bias in credit decisions in the USA. Specifically, the study provides evidence that banks' adoption of FinTech algorithms can significantly increase female loan approval rates and reduce gender inequality in bank loans. The study uses a rigorous two-step system GMM approach and Difference in Difference analysis to estimate the effect of FinTech algorithms on gender bias in credit decisions, controlling for other factors that may affect loan approval rates.

The findings of this study have significant implications for policymakers and financial service providers. Our results suggest that adopting FinTech algorithms can be a powerful tool for promoting gender equality in financial services by reducing gender bias in credit decisions. Policymakers can utilise these findings to promote the widespread adoption of FinTech algorithms in banks and other financial institutions. Financial service providers can also leverage these results to guide their adoption of FinTech algorithms and develop strategies to mitigate gender bias in credit decisions. These actions could ultimately lead to greater financial inclusion and equal access to credit for all individuals, regardless of gender.

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