ESSAYS ON ALTERNATIVE CREDIT: ITS EVOLUTION AND IMPACT ON LENDING MARKETS AND FINANCIAL STABILITY

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1 Introduction

I would like to begin by expressing my sincere gratitude to the reviewers for their time, effort, and thoughtful insights into evaluating my doctoral dissertation. Your comments have been extremely useful in helping me sharpen the analytical focus, strengthen the empirical contributions, and clarify the presentation of the material. The constructive nature of your feedback has had a meaningful impact on the overall quality of the manuscript.

In responding to your observations, I have approached each point with careful attention and a genuine effort to engage critically and improve the work. Where limitations remain or where further refinement may still be needed, I welcome the opportunity to learn from your expertise. Your guidance has been invaluable in shaping both the substance and structure of this dissertation.

In what follows, I provide brief responses to each comment raised, and for ease of reading, my responses are provided in blue text. Page numbers refer to the outer page numbers in the PDF.

2 Responses to Comments by Prof. Valenti on Chapter 1

2.1 First Chapter titled: "The GDPR Disruption: The Impact of Data Privacy Regulation on the Alternative Credit Market."

1. On page 2, the candidate should better define and explain the meaning of credit extension or alternative credit.

   Response: Alternative credit is now explicitly defined in the General Introduction (page 2), briefly outlining its scope. A more detailed explanation is provided in Chapter 1, Section 3.1 (page 27), and Chapter 2, Section 4.1 (page 105), where the term is clearly articulated along with its components, data sources, and relevant transformations.

2. On pages 4,5 and 6, the candidate describes his contributions to the existent literature. However, it not clear what are the main novelties of the paper. Instead of discussing about what others do, the candidate should clarify properly what his contribution to the literature. For example, on page 5 the candidate state:

   "However, our study differs from the above studies in the following ways. First, most of the studies (Boissay et al. (2021),Carstens (2018),Feyen et al. (2021),Petralia et al. (2019)) discussed privacy (regulation) and penetration of the FinTech and BigTech firms and the credit extended by these firms only qualitatively."

   At this point in the Introduction, the reader expects a clear articulation of the research gap addressed by this work. Specifically, this paper provides a methodological contribution to examining the impact of data privacy regulation on the market penetration of FinTech and BigTech firms and their combined credit extension activities.

I have substantially revised the entire Introduction section to enhance clarity, coherence, and alignment with the dissertation's core objectives. I kindly invite the esteemed examiners to review the updated Introduction in its entirety.

- Discuss the main advantages of using quasi-experimental methods in this context compared to other quantitative or qualitative approaches.

  Thank you. This is covered as well in the Introduction section. However, a detailed explanation is given in the Empirical strategy section starting on page 114

- Provide a rationale for employing Difference-in-Differences (DiD), Synthetic Difference-in Difference (SDiD) and Synthetic Control Method (SCM) to analyze the impact of data privacy regulation on the overall volume of alternative credit. Highlight how these methods address issues of causal inference by comparing pre- and post-regulation trends between treated and untreated groups, or by constructing a counterfactual scenario to isolate the regulation's effect.

  Thank you. This is covered in the introduction section as well.

a. *Second, there is a scope difference in geographical area coverage and the type of credit considered alternative credit. Most of the above studies focused either on the FinTech or BigTech credit market.* *Our analysis focus on both FinTech and BigTech credit and their combined credit, called alternative credit.* *Even from the FinTech credit market, most studies consider peer-to-peer credit as the only FinTech credit.* Why it is not better to consider the SDiD as a benchmark and the DiD as a robustness check?

I have provided a brief discussion in the Introduction section and a detailed explanation on the Empirical strategy section starting on page 114.

b.The authors should emphasise better the strengths and the weakness of the two approaches and explain the reasons behind the first option.

This is addressed in the same Empirical Strategy section starting on page 114.

c. What are the main differences between SCM and SDiD?

Explanation provided on the same section. Thank you

Expand the discussion on the significance of encompassing all forms of digital lending within the FinTech sector, emphasizing how this approach captures the diverse mechanisms and innovations driving the industry. Clearly articulate why your analysis stands out as more comprehensive and exhaustive compared to existing studies, highlighting its inclusion of multiple lending models, robust methodology, and broader insights into the impact of digital lending on credit markets.

"Third, the Study by Doerr, Gambacorta, et al. (2023), Gambacorta et al. (2022), and others focused on a single market (US, China, or other countries). To our knowledge,Cornelli et al. (2020) and Frost et al. (2019, 2020) are the few cross-country analyses for the alternative credit market and sought to explain the determinants of BigTech credit volumes in a cross-country setting. However, these studies are limited to investigating the determinants of the alternative credit market"

Instead of emphasizing the limitations of other studies, the candidate should focus on clearly explaining and highlighting the strengths of their own work, with particular focus on panel-data (multi-country) approach.

This is a valuable comment, thank you. The manuscript has been updated accordingly.

3. On page 5: *"To our knowledge,Cornelli et al. (2023) . . . " or "To our knowledge the study by Doerr, Frost, et al. (2023)"*. Avoid using the phrase "to our knowledge" as it may appear inappropriate. Replace it with a more assertive or objective statement, such as "This study is the first to address..."

   This is a valuable comment, thank you. The manuscript has been updated accordingly.

4. On page 6: The discussion of results should be enriched by including relevant quantitative estimates. This not only adds precision and clarity to the findings but also strengthens the argument by providing concrete evidence to support the conclusions drawn from the analysis.

   Corrected.

5. In Section 2, on pages 11 and 12, the Candidate should focus exclusively on the literature review, presenting a comprehensive overview of relevant studies in the field. The detailed contribution of his work should be removed from this section and instead be thoroughly discussed in the Introduction, where it is more appropriately placed.

   Corrected and improved accordingly.

6. In section 4.1, the candidate should provide a clearer and more detailed description of the data used in the analysis, particularly the variable of interest. This can be addressed by incorporating the following clarifications:
   This section also has been improved substantially to address the raised concerns and comments

   a. Definition of Alternative Credit: Specify whether alternative credit is defined as the sum of FinTech and BigTech credit or if it includes other forms of credit as well. If it encompasses additional categories, list and briefly describe them.

   The entire methodology section has been corrected accordingly.

   b. Unit of Measure: Clearly state the unit of measure for all variables (e.g., dollars, percentage of GDP, or other metrics). This helps contextualize the scale of the data and ensures consistency. Are these variables subject to any transformations (log-variable, log-diff ect.) Why?

Addressed in the data and Variable Description Section on page 105.

c. Data Transformations: Explain if any transformations (e.g., logarithms, log-differences, standardizations) are applied to the variables. Justify these transformations, detailing how they improve the analysis (e.g., handling skewed distributions, ensuring stationarity, or interpreting growth rates).

Addressed in the data and Variable Description Section on page 105 through 110.

d. Number of Countries and Selection Criteria: Indicate the total number of countries included in the analysis and explain the rationale behind their selection (e.g., data availability,regional focus, economic relevance). Provide a summary table if necessary to outline the geographic coverage.

Summary Table on page 149 and detailed discussion has been included in the Empirical Strategy section on page 114

e. Visualization of Data: Include a plot that illustrates the trends of FinTech, BigTech, and Alternative Credit over time. Ensure the graph is clear, labeled, and includes a brief explanation of the observed patterns (e.g., growth trends, divergences, or convergence). Discuss any noticeable tendencies in the data, such as sharp increases or decreases, and relate these to potential factors like policy changes or economic shocks.

I have introduced a section titled "Descriptive Statistics and Stylized Facts" on page 110 and discussed graphs and tables in detail.

These additions will clarify the scope, structure, and trends of the data, making the analysis more transparent and robust for the reader.

7. In section 4.2, the candidate opts for a DiD estimation as the benchamark compared to the SDiD. Why?

    a. On page 22 the Candidate states "Empirically, Arkhangelsky et al. (2021) find that the SDiD method competes with (or dominates) DID and SC in applications."

        i So, why do not consider the SDiD method as the benchmark model for the analysis? To further strengthen the study's credibility, results from traditional DiD can be presented as a robustness check.

        Explanation provided in the Empirical Strategy section. Thank you.

        ii What are the main differences between SCM and SDiD?

        Explanation provided in the Empirical Strategy section. Thank you.

        iii Why do not estimate also the SCM for your study?

Explanation provided in the Empirical Strategy section. Thank you.

8. Do equations 1.8, 1.9 and 1.10 describe the optimal rule for choosing the counterfactual?

    a. Why in case of SDiD you don't consider the lagged values of Yit to improve the match between treated and control units?

    Corrected.

    b. Why do not use a proabaility score matching in case of DiD estimation?

    Matching has been introduced and done through Entropy matching. Explanation is given on page 119

9. Include a dedicated section to discuss the primary policy implications of your findings.

    The Conclusion section has been revised to include a discussion of relevant policy implications. The title also changed to "Conclusions and Policy Implications" and implications are incorporated alongside suggested avenues for future research.

10. Minor comments:

    a. Check the notes on Tables.

        i. Example: Table 1.1. This table reports results for Equation 1.5. The dependent variables are the log of FinTech credit (column 1), BigTech credit(column 1), and alternative credit(column 3).

Corrected.

Comments on the Second Chapter

1. The Candidate should revise Section 1 (Introduction) by restructuring it for clarity and conciseness, while integrating the contributions currently outlined in Section 2 into the Introduction. Remove the subsection Contribution of the study from the Literature review.

I have substantially revised the entire Introduction section to enhance clarity, coherence, and alignment with the dissertation's core objectives. I kindly invite the esteemed examiners to review the updated Introduction in its entirety.

Section 3.1 is not sufficient. To ensure clarity and depth, dedicating a specific section to Data and Variables is essential. a. Begin with a clear and concise overview of the dataset(s) used in the analysis. b. Mention the source(s) of the data and their relevance to the research objectives. c. Provide a detailed description of all variables. d. Move and integrate the section titled Descriptive Statistics into the Data section for a more cohesive presentation

I have substantially revised the entire Data, Methodology and Empircal Framework section and it addressed all the questions. Thank you very much for the guide

Methodology: Section 3.2: The impact of alternative credit on bank credit supply. The candidate should explore different estimation techniques that might fit better the properties of the data. And Section 4.2: The relationship between Alternative Credits and Conventional Bank Credit a. It is not entirely clear how Equation 2.2 allows for the disentanglement of bank credit supply from bank credit demand. Please provide a detailed explanation or clarification regarding this distinction. b. Why does the proxy for the Covid-19 outbreak enter the model as a lagged variable, given that this variable is exogenous by definition? i. Did you also test alternative proxies for the Covid-19 outbreak, such as hospitalizations (e.g., Ng, 2021)? If so, do you believe the results would remain consistent across different proxies? c. Given the inclusion of 145 countries in the analysis, why not account for unobserved heterogeneity by clustering similar countries and using a group fixed-effect estimation, as proposed by Bonhomme and Manresa? This approach could provide a more structured way to capture shared characteristics among similar countries d. Moreover, why not consider a dynamic version of Model 2.2? It is reasonable to assume that the volume of traditional bank credit is significantly influenced by its own past values. To address this, the Candidate should provide results using appropriate estimation methods that account for endogeneity issues, such as the 'Half-panel jackknife fixed-effects estimation of linear panels with weakly exogenous regressors,' as developed by Chudik et al. (2018).“ My suggestion – if the Candidate deems necessary – is to provide empirical estimates using alternative estimation techniques that differ from “canonical” fixed-effect panel data estimation and to compare the results across these methods.

All the comments are addressed in the Methodology chapter. Thank you.

Add relevant policy implications to the conclusions and rename the section as Policy Implications and Conclusions to reflect its broader scope

The Conclusion section has been revised to include a discussion of relevant policy implications. The title also changed to Conclusions and Policy Implications and implications are incorporated alongside suggested avenues for future research.

3 Responses to Comments by Prof. Saraceno on Chapter 1

Essays in privacy regulation, alternative credit, and financial stability-PhD Thesis (#855188)

Thesis structure

Although the two papers are presented as independent studies, they are based on very similar datasets. Moreover, they analyze some interconnected empirical questions. My suggestion is to switch the two papers. In fact, the second paper is more general than the first one and deals with very standard issues. It can help the reader to better understand what the alternative credit is and then to appreciate the issue studied in the first paper (the impact of GDPR on the alternative credit).

Concerning the title of the thesis, the focus on privacy regulation looks disproportionate. My suggestion is to revise the title, focusing on alternative credit. Something like Essays on *Alternative Credit: Its Evolution and Role in the Lending Market and Financial Stability* ccoul work. Actually, the first paper, though aimed at verifying the impact of GDPR enactment on FinTech and BigTech lending, cannot be considered a paper on privacy regulation.

This is a valuable comment, thank you. The manuscript has been updated accordingly, including the title. Thank you very much.

Language and narrative

A careful proofreading of the two papers is strongly advised. There are several typos (missing brackets, missing spaces, word repetitions) and spelling mistakes. Sometimes reading is not fluent. Wording can be improved; some sentences are not understandable [e.g., p. 85, "To understand that results are not driven up such economies"; this sentence is probably the continuation of the previous sentence], or imprecise [e.g., p. 88, about covid, there is "instability" instead of "stability," etc.]

This is a valuable comment, thank you. The manuscript has been updated accordingly.

Please avoid repetitions (especially in the second paper). The author has to be more precise when explaining what the analysis is about and when defining the variables. E.g., what exactly does "alternative credit" mean? Please, immediately clarify that it is the per capita credit that is provided by FinTech and BighTech companies, then clarify data sources, the unit of measurement (if I am correct, it is completely missing), etc. The reader has to put in a lot of effort to clearly understand what the author is actually analyzing. This is true for several concepts and variables. The author should provide a straightforward explanation about what is going to be tested (see detailed comments below). Also, the explanation of the methodology should be improved, especially in the second paper, where the strategy of variable inclusion in the first and the second stage has to be clarified.

This too is a very valuable comment, thank you. The manuscript has been updated accordingly.

Sometimes comments on the results and references to the previous literature are redundant. Often, results' implications look like a long shot. Even if the reader would be sufficiently persuaded that the GDPR enactment positively affected alternative credit, they might have some doubts about the idea that the main driver of this positive effect is the increased trust in users about data management. The latter point is not proved empirically. Redundancy (especially in the second paper) and too ambitious implications make the two papers a bit chaotic. My general suggestion is to revise both papers by cleaning the narrative and preparing very straightforward sections [Intro, Lit., Hypotheses to be tested, Variables and data description (including clear variable definitions, units of measurement, and sources of data, etc.), Methodology, Results, Robustness checks, Conclusions]. Implications should be discussed in more cautious terms. The suggested format has been followed and it really improved the paper for concisesnee and reducing redundancy. Thank you

Specific comments *on The GDPR Disruption: The Impact of Data Privacy Regulation on the Alternative Credit Market*

I appreciate the idea of the paper: it is sound to assume that a disruptive law like GDPR can have a significant impact on several sectors and along different dimensions. However, I have some concerns about the overall approach.

In particular, the underlying idea is that potential borrowers are more prone to demanding credit from FinTech and BigTech after the enactment of the GDPR because they are more confident about data management and protection by part of these companies. On the other hand, FinTech and BigTech can supply market segments that are not served by traditional banking thanks to credit scoring models that exploit larger sets of users' data. This is a possibility for sure. However, the methodology cannot allow testing (and disentangling the role of) these hypotheses.

1) As well shown in previous literature, per se, the enactment of a law often does not significantly change the perception of breach risk by part of regulatees among people who the law is aimed to protect. Rather, the effective law enforcement can promote confidence in fair behavior. The author even investigates the

   effect of law anticipation without finding any interesting result. This is not surprising because users hardly change their perception of breach risk when a law is simply announced; probably only a massive actual compliance with the GDPR (occurred in the countries under the jurisdiction of the GDPR in different moments, first in some sectors, later in others) might have a nonnegligible effect on trust. On this point see, for example,Bhattacharya and Daouk (2002) ,La Porta et al. (2006) ,Leuz and Wysocki (2016) etc. Moreover, the author includes a trust measure among the control variables. Therefore, I am not convinced that the observed positive GDPR effects on alternative credit are mainly driven by the trust of borrowers in data management by part of the FinTech and BigTech. Moreover, evidence from BigTech credit is less clear-cut. This difference between FinTech and BigTech can hardly be explained by recourse to the trust driver. It would be important to look at the impact of GDPR (possibly its enforcement) on total lending and then on alternative lending (by distinguishing between FinTech and BigTech that provide very different kinds of credit) relative to total lending to collect more useful insight about the possible drivers of the observed positive effects.

   This detailed comment has been incorporated in the entire section of the chapter

2) There are other hypotheses that should be considered.

- Compliance with GDPR by part of the firms has likely reduced the uncertainty that firms face about the use (and abuse) of data. Compliance with GDPR could have even reduced expected litigation costs and provided firms with a frame to manage (and exploit) data at lower costs in the medium term (after a possible initial cost increase due to compliance). On this point, I suggest seeing the literature on the *value of compliance* (see Almeida Teixeira et al. (2019) and others about regulatory compliance). I guess that, though with different intensity, several sectors benefited from the GDPR enactment/enforcement. Some sectors, especially those intensively regulated and supervised, including banking and financial sectors, can implement GDPR compliance at lower costs and with higher benefits. (See also the relationship between GDPR compliance systems and RegTech and SupTech). It would be interesting to verify what happened to both the total credit and then the alternative credit. Overall, total lending (including traditional lending) might be positively affected by the enactment of GDPR and, possibly, alternative credit relatively more because FinTech and BigTech have been more (much more FinTech and less BigTech) able to extract benefits from the GDPR. See Geradin et al. (2021), Blind et al. (2024), Ullagaddi (2024). Along this line, the issue of the GDPR's impact on competition must be carefully considered too, possibly at the empirical level. According to part of the literature, the GDPR favored the lawful exploitation of data functional to price discrimination. The author briefly discusses the point and mentions previous literature; however, the price discrimination driver is not deepened at an empirical level. See Gal and Aviv (2020) Gal and Aviv (2020) and Johnson et al. (2023).

Thank you again for this comment. I have included a discussion on the topic throughout the chapter. I introduced a complance measurment in the study as well

- Along this line, the issue of the GDPR's impact on competition must be carefully considered too, possibly at the empirical level. According to part of the literature, the GDPR favored the lawful exploitation of data functional to price discrimination. The author briefly discusses the point and mentions previous literature; however, the price discrimination driver is not deepened at an empirical level. See Gal and Aviv (2020) and Johnson et al. (2023)

  These alternative/complementary drivers should be (at least) properly discussed.

Concluding,

a) The author should be more precise in presenting the hypothesis to be tested, the variables (variable definitions must be significantly clarified), and data in use (please specify unit of measurement, currency, etc.). This is also needed for the control variables. Also, the wording must be more precise; it is often difficult to understand what the author is actually analyzing (e.g., the author uses "penetration," "extension," "volume," "value," and "market shares" of *alternative credit* more or less as synonyms). Corrected.

b) The empirical analysis could be improved if carried out by looking at the relative weight of alternative credit (distinguishing between FinTech and BigTech credit) on total credit (including traditional banking credit). The effects of GDPR on total credit cannot be neglected, also considering the complementarity and/or substitutability relationship between alternative and banking lending. It is done and incorporated in the discussions.

c) Results show that GDPR had a different impact on FinTech credit and BigTech credit. This difference should be deepened. Implications should be revised in more cautious terms.

It is done and incorporated in the discussions.

Specific comments *on Disruptive Forces or Harmonious Partners? Unraveling the Role of Alternative Credit in Financial Stability and its Relation with Conventional Credit Credit in Financial Stability and its Relation with Conventional Credit*

1) I suggest moving this paper first. It must be deeply revised. It looks not sufficiently polished. The introduction and the literature review partially overlap. Many statements and sentences are redundant. Data description must be significantly improved: please clarify variable definitions, data sources, and units of measurement (at least, detail Table B1; there are also typos/imprecisions: see "Alternative credit" defined as "Alternative credit per capita GDP is the sum of BigTech and FinTech credit").

   Corrected.

2) The competition and price discrimination issues raised for the first paper joint with financial inclusion and diversification are very relevant in the present paper. Competition, financial inclusion, diversification, and financial stability have a complex relationship (neither linear nor univocal). See Goodhart (2006), Noman et al. (2017),(2021),Kim et al. (2020). Moreover, the effects of digital transformation and diversification on financial stability are non-linear and depend on several factors.

   The authors should carefully and methodically discuss these issues, clarifying what he can get from both his analysis and the resulting empirical figures. Results should be compared with the extant literature. Implications should be cautiously derived from the empirical evidence.

   Included in the discussion. Thank you

3) Endogeneity is managed through a standard IV approach; the instrument variable consists in the mobile subscriptions and fixed broadband subscriptions. The author justifies that choice based on the previous literature. I think that the author should devote more effort to justifying why mobile and broadband subscriptions can represent a good instrument. Although standard tests support this IV, I am not so sure that it can solve endogeneity issues properly. In particular, a reader could have many doubts about the soundness of the instrument because both alternative credit and traditional credit development and GDP growth can all be simultaneous. On the other hand, the use of a one-year lag for control variables (due to yearly data) looks quite long. The author should better support his IV choice by reasoning and not only using tests and literature precedents. Detailed explanations might help the reader to appreciate the selected instrument. Additional effort

should be devoted to the explanation about how control variables have been selected. This last point has to be carefully managed.

From the methodological perspective, I do not understand the ratio of control variable inclusion. Control variables included in the first stage are usually the same as those that are included in the second stage. In standard 2SLS, in the first stage, each endogenous variable is regressed against the exogenous variables, and then the fitted value is used in the second stage along with the exogenous variables. The inclusion strategy in the two stages is really confounding. Regressors included in the two stages are completely different. This makes estimates unreliable, or, at least, difficult to be properly understood. The strategy to use lags should be deepened, as well. My overall impression is that the empirical strategy is unclear.

I acknowledge that the initial manuscript contained an error in the specification of the variables included in the first and second stages of the instrumental variable estimation. This has now been corrected in the revised version. Thank you very much for your valuable observation.

4) Moreover, some specific controls can be improved. For example, the impact of Covid could be assessed by using more precise information (see, for example, the Oxford Coronavirus Government Response Tracker project). The *Ease of doing Business* is also a debatable source of data (the series changed a lot over time; there are problems of comparability year by year, etc). Think about a more parsimonious estimates.

Both variables are improved and discussed in detail in the variable description section.

Overall, I think that this paper could strongly benefit from a deep revision, including the formulation of a sort of model able to grasp what the author wants to test and supporting the strategy for regressors' inclusion. I am not suggesting developing a theoretical model, but at least a clear theoretical framework to guide the empirical questions. Reducing the number of control variables might be beneficial.

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ESSAYS ON ALTERNATIVE CREDIT: ITS EVOLUTION AND IMPACT ON LENDING MARKETS AND FINANCIAL STABILITY

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To my parents, siblings, and partner—you helped and sacrificed more than I could have ever asked for. Thank you for everything. I hope this makes you proud.

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God is good. All the time!

Introduction

This thesis consists of two standalone chapters that empirically investigate distinct research questions. Despite their independence, both chapters are thematically connected through their exploration of the alternative credit market. Alternative credit refers to lending activities carried out by non-traditional financial intermediaries, primarily Financial Technology (FinTech) and BigTech firms. FinTech credit encompasses digital lending models such as invoice trading and peer-to-peer (P2P) or marketplace lending, which operate through online platforms rather than conventional banks or lending institutions (Claessens et al., 2018; Cornelli et al., 2023). It is also referred to as debt-based alternative finance (Wardrop et al., 2015). In recent years, BigTech firms have also entered the credit market, either by lending directly or through partnerships with financial institutions, creating what is now known as BigTech credit (Cornelli et al., 2023). FinTech and BigTech credit collectively constitute what is broadly referred to as alternative credit.

The first chapter is titled "Disruptive Forces or Harmonious Partners? Unraveling the Role of Alternative Credit in Financial Stability and Its Relation with Conventional Credit." It focuses on the macroeconomic consequences of alternative credit. The chapter first highlights important dynamics in the rise of alternative credit. It specifically examines whether alternative credit substitutes or complements conventional bank credit and the effect of an external shock on such a relationship. Second, it investigates the role of these forms of alternative credit in financial stability. To address these research questions, I utilize a panel dataset of 1,024 observations across 145 countries from 2013 to 2020. To address these questions, I employ a Two-Stage Least Squares (2SLS) estimation method, along with the Half-Panel Jackknife Fixed Effects (HPJ-FE) estimator and the Grouped Fixed Effects (GFE) model, to ensure robustness against endogeneity, dynamic panel bias, and unobserved heterogeneity across countries. The study finds a positive relationship between alternative forms of credit (FinTech and BigTech credit) and traditional bank credit, indicating a complementary dynamic. This complementarity may stem from the alternative credit market's ability to serve credit demands beyond the reach of conventional banks—either by addressing the needs of un(der)served borrowers or fostering alliances between banks and technology firms to enhance credit extension. These developments can enhance efficiency, lower screening costs and time, and improve access through digital channels. The study also shows that external shocks such as the

COVID-19 pandemic negatively impacted bank credit supply and may have weakened the complementarity between alternative credit and bank credit. I additionally show that alternative credit contributes modestly to financial stability, possibly due to diversification and technological innovations that enhance market efficiency, reduce transaction costs, and limit vulnerability to systemic institutional failures. However, external shocks such as the pandemic appear to increase the fragility of the banking system and diminish the gains observed during stable periods.

In the second chapter titled “The GDPR Disruption: The Impact of Data Privacy Regulation on the Alternative Credit Market,” I examine the impact of data regulation on credit extension by FinTech and BigTech firms. It is the first to empirically investigate how the General Data Protection Regulation (GDPR), a privacy regulation implemented in all European Union member states in 2018, shrinks firms’ flexibility in data storage, sharing, and usage, and affects the alternative credit market. The study covers the period between 2013 and 2020 and employs a Difference-in-Differences (DiD) approach to estimate the causal effect of tighter data privacy regulations on the European alternative credit market.

The net effect of GDPR on alternative credit is theoretically ambiguous. While it may reduce supply by increasing compliance costs and limiting access to granular data, it could also boost demand by enhancing consumer trust in financial technologies and regulatory institutions, as well as by reinforcing the market consolidation of established technology firms. The empirical result indicates that FinTech credit responds positively to the implementation of the GDPR, suggesting that data protection regulations can benefit FinTech lenders. However, no significant effect of GDPR on BigTech credit is observed. This likely reflects that potential reputational gains from compliance are delayed or diluted by persistent consumer concerns over data misuse, high compliance costs, and intense regulatory scrutiny, all of which constrain credit supply. Additionally, unobserved factors such as firms’ compliance strategies, market positioning, and capacity to absorb regulatory shocks through scale and diversification may explain the lack of impact.

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Chapter 1: Disruptive Forces or Harmonious Partners? Unraveling the Role of Alternative Credit in Financial Stability and its Relation with Conventional Credit

Abstract

The rise of FinTech and BigTech lending has reshaped global credit markets, positioning alternative credit as both a disruptor and a partner to traditional banks. This chapter examines the interaction between alternative and conventional credit, as well as its implications for financial stability, using panel data from 145 countries spanning 2013 to 2020. It also explores how these relationships evolve under exogenous shocks, such as the COVID-19 pandemic. Employing a Two-Stage Least Squares (2SLS) method to address endogeneity, the analysis identifies a complementary dynamic between alternative and conventional credit, likely attributable to market segmentation or efficiency-driven partnerships. The results further indicate that the pandemic weakened this complementary relationship and negatively affected conventional bank credit supply amid heightened risk aversion. Additional analysis using a two-way fixed effects model and 2SLS as a robustness check shows that alternative credit modestly mitigates banking system fragility through diversification and operational efficiencies. However, external shocks such as the pandemic diminish these observed gains.

Keywords: Alternative credit, Conventional Bank credit, COVID-19, External shock, Financial Stability.

1 Introduction

The global financial landscape is undergoing a seismic shift as FinTech platforms and BigTech firms redefine credit markets through algorithmic lending. Once dominated by brick-and-mortar banks, these markets now intertwine with digital-native lenders, blurring boundaries between banks and non-banks. Alternative credit providers—once disruptors—are now deeply embedded, filling gaps left by lending cuts and expanding digital-first access to underserved borrowers. Yet critical questions loom: Are these providers destabilizing forces amplifying systemic risk, or harmonious partners forging a more resilient credit ecosystem? This convergence, where banks engage with non-bank lenders as both competitors and collaborators, raises new concerns about systemic risk and the future of financial intermediation.

Recent developments highlight the scale and complexity of the credit market transformation. In the United States, traditional banks have sharply increased lending to non-bank financial institutions, raising concerns about systemic risk. According to the *Financial Times*[1] (2025), *"There is a growing interconnectedness between traditional banks and alternative credit providers... That has put private credit firms in direct competition with banks while also turning them into some of their most important clients by providing the leverage that helps boost returns... US banks' significant increase in their lending to non-bank financial institutions raises concerns of systemic risks."*

Meanwhile, small and medium-sized enterprises (SMEs) increasingly rely on FinTech platforms for financing. In the United Kingdom, for example, SMEs have faced mounting difficulties in obtaining bank loans due to rising debt burdens. According to *The Times*[2] (2025), *"SMEs have faced challenges in accessing traditional bank loans due to increased debt burdens... This has led to a greater reliance on alternative credit sources, such as FinTech platforms."* Similarly, *The Fintech Times*[3] (2021) notes that *"Approximately 9.3 million UK adults considered using open finance over traditional banks to access credit."* These examples underscore alternative credit's dual role—disrupting banking norms while addressing unmet demand, with profound implications for credit allocation and financial stability.

[1] https://www.ft.com/content/8da75eba-bf80-4d31-ba49-1a4133e390c0

[2] https://www.thetimes.com/business-money/companies/article/debt-load-of-businesses-seeking-finance-is-double-pre-covid-level-5xzst9njt

[3] https://thefintechtimes.com/fintech-lending-options-are-overtaking-traditional-banks-clearscore-data-reveals/

At the core of this shift lie FinTech and BigTech credit models. Digital lending methods—such as invoice trading, peer-to-peer (P2P), and marketplace lending—use online platforms as intermediaries rather than conventional banks. These models fall under the term FinTech credit (Claessens et al., 2018; Cornelli et al., 2023), also known as debt-based alternative finance (Wardrop et al., 2015). Recently, BigTech firms entered credit markets, lending directly or partnering with financial institutions (Cornelli et al., 2023). This form of lending by BigTech firms is referred to as BigTech credit. Collectively, FinTech and BigTech lending activities constitute alternative credit.

Understanding the characteristics of FinTech and BigTech credit is essential to analyze their influence on credit markets. While both innovate access, key differences persist. FinTech platforms primarily offer financial services. They present investors with borrowers and risk data and function as decentralized markets where lenders select borrowers or projects (Cornelli et al., 2020; Jagtiani & Lemieux, 2019). In contrast, BigTech firms provide credit alongside non-financial services (Doerr, Gambacorta, et al., 2023; Frost et al., 2019), leveraging large user bases and non-financial data to streamline onboarding and reduce information asymmetry. This enables them to effectively assess loan quality and minimize defaults (Cornelli et al., 2020).

Despite these differences, both rely on advanced credit assessment using large, diverse data sources. FinTech and BigTech firms employ machine learning-based credit scoring models, often referred to as a new credit scoring model (Jagtiani & Lemieux, 2019). These models incorporate alternative data—including geolocation (Carstens, 2018), transaction history (Feng et al., 2021; Frost et al., 2019), social media activity (Q. Fang et al., 2015), digital footprints (Berg et al., 2020), customer reviews (Frost et al., 2019), and phone or email history (Cornelli et al., 2022). The machine learning-based new credit scoring model can capture the non-linear information from variables and predict losses and defaults better than the Logit model-based traditional credit scoring model in the presence of a negative shock to the aggregate credit supply, enhancing financial inclusion and stability.

Similar market factors shape both FinTech and BigTech credit. Economic activity, competitiveness, and financial and data regulation influence their development (Frost et al., 2019). Cross-country studies (Cornelli et al., 2020; Frost et al., 2019) show greater alternative credit activity in countries with higher (but tapering) GDP per capita, fewer bank branches per capita, higher banking markups, and more advanced investor protections.

Alternative credit also flourishes where doing business is easier, banking regulation is less stringent, and capital markets are more developed.

According to the Cambridge Center for Alternative Finance (CCAF), global FinTech credit expanded from under USD 10 billion in 2013 to over USD 120 billion by 2020, with China, the United States, and the United Kingdom leading this growth (CCAF, 2021; Cornelli et al., 2020). While smaller in absolute terms, regions such as Latin America and the Caribbean experienced rapid growth, particularly in Brazil and Mexico, driven by high mobile penetration and gaps in traditional banking. BigTech credit by large technology firms such as Ant Group, Amazon, MercadoLibre, and Tencent has grown even faster. The Financial Stability Board estimated its global volume at USD 572 billion in 2019, with China leading in the race (FSB, 2019), while increasing in Latin America, Southeast Asia, and the US. For example, Amazon Lending issued over USD 5 billion to US-based SMEs by 2021, while Mercado Crédito's outstanding loans surpassed USD 2.4 billion across Latin America (Bains et al., 2022; BIS, 2022).

This paper examines two core questions related to alternative credit. First, this paper tracks the rise of alternative credit, assessing whether it can replace or complement traditional credit. Second, it investigates the role of alternative credit on financial stability. I also test how these relationships are affected by large exogenous shocks such as the COVID-19 pandemic. It is the first to empirically investigate the relationship between banks and alternative credit across a large, cross-country panel of 145 countries. This broad scope captures global dynamics and cross-country variation in the interaction between alternative and traditional credit and their implications for financial stability.

Several empirical studies have examined the relationship between alternative credit and bank credit supply, but they have largely been limited to specific markets or lending segments. Most focus solely on either FinTech Hodula (2022) or BigTech credit, often narrowing further to specific FinTech segments like P2P lending (de Roure et al., 2021; Jagtiani & Lemieux, 2019; Lee et al., 2021; Sheng, 2021; Tang, 2019) or crowdfunding (Cole et al., 2019) and their effects on bank lending. In contrast, this study adopts a more comprehensive approach and incorporates both FinTech and BigTech credit and their combined impact on conventional bank credit supply. Additionally, while most studies focus on specific forms of FinTech lending like P2P and crowdfunding, this study takes a broader approach by including all types of digital lending identified as FinTech credit in the CCAF database[4]. This broader inclusion offers a comprehensive view of the credit market and reveals overarching trends and patterns that may not be apparent when examining specific lending forms. This approach captures structural shifts from relationship-based to platform-based lending, including platform scale effects and the implications of credit model innovations on risk distribution. Unlike single-country microstudies focusing on the US (Jagtiani et al., 2021; Tang, 2019), Germany (de Roure et al., 2021), or China (Sheng, 2021), it provides cross-country comparative analysis. Moreover, by focusing on macro-level data across countries, this study uncovers global patterns that single-country or firm-level studies may miss, and uniquely examines how external shocks reshape the interaction between bank credit and alternative credit, and their joint implications for financial stability.

The second focus of this chapter is the impact of alternative credit on financial stability. While traditional financial crises often stem from excessive leverage, risk-taking, or asset bubbles (Brunnermeier & Oehmke, 2013), technological disruption introduces new risks by shifting activities outside the scope of prudential regulation (Petralia et al., 2019). Strict data regulations, such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA), aim to address these evolving challenges.

According to FSB and CGFS (2017), the small scale of alternative credit relative to traditional credit limits its direct impact on financial stability across major jurisdictions. However, a larger market share could present a mix of financial stability benefits and risks. Benefits include greater financial inclusion, credit diversification, and efficiency pressures on incumbents. The alternative credit model, which uses the new credit scoring to better estimate default risk and losses compared to traditional credit bureaus, enhances financial stability and inclusion (Gambacorta et al., 2024).

Among the risks are a potential deterioration of lending standards, increased procyclicality of credit provision, and a disorderly impact on traditional banks, for example, through revenue erosion or additional risk-taking (FSB & CGFS, 2017). A particular segment of consumers may also be disproportionately unfavored by introducing machine learning in credit scoring models (Fuster et al., 2022; Petralia et al., 2019) as machine learning algorithms may be able to extract sensitive information based on geographical location

[4]CCAF's FinTech credit include Balance Sheet Lending (Balance Sheet Business Lending, Balance Sheet Property Lending, and Balance Sheet Consumer Lending), P2P / Marketplace Lending (such as Marketplace Consumer, P2P Business Lending, P2P Property Lending), Debt-Based Securities and Mini-Bonds, and Invoice Trading

(Carstens, 2018), buying patterns (Feng et al., 2021), social media activity (Q. Fang et al., 2015). Biases in these algorithms may result in discrimination based on race, religion, or other factors, and can exacerbate inequality (Fuster et al., 2022; O'neil, 2017).

From a policy perspective, two broad schools of thought exist regarding the relationship between market dynamics and financial stability (BIS, 2019; Doerr, Frost, et al., 2023). One argues that the entry of new players, including FinTechs and BigTechs, can enhance competition, diversify services, and reduce systemic risks tied to large, concentrated institutions (Amidu & Wolfe, 2013; Feldman, 2010). The other cautions that unchecked entry and heightened competition may erode profits, induce risk-taking, and leave traditional institutions with riskier, loss-making businesses, ultimately threatening financial stability (Feyen et al., 2021; Hellmann et al., 2000).

More recent research suggests that the emergence of FinTech and BigTech credit reshapes this relationship by introducing new mechanisms called Data-Network-Activity (DNA) feedback loop (BIS, 2019; Doerr, Frost, et al., 2023; Feyen et al., 2021). Network externalities attract more users, enhancing platform value for all participants and enabling tech firms to accumulate additional data. Analyzing large volumes of data improves service quality, drawing in additional users. This expanding user base creates a critical mass, allowing platforms to diversify their service offerings, generating even more data (Boissay et al., 2021).

BigTech firms often leverage dominance in their non-financial markets to gain footholds in credit markets. Their control over critical infrastructure, such as networks and cloud services, allows them to entrench their position and influence financial market dynamics. When traditional financial institutions depend on platforms owned by BigTech competitors for service delivery infrastructures, conflicts of interest and risks of market abuse may emerge, posing unique threats to financial stability (BIS, 2019; Doerr, Frost, et al., 2023; FSB, 2019).

Prior research, such as Philippon (2016), has theoretically discussed the potential impact of FinTech on financial stability and service access, while Carstens (2018) emphasized the systemic risks posed by digital financial products like online Money Market Funds. Vuković et al. (2024) and Fung et al. (2020) examined the FinTech–stability link but focused on BRICS or bank-level data, respectively. Other works (Daud et al., 2022; Khan et al., 2023) analyzed broader technological innovation, such as artificial intelligence, cloud, and data technologies, without directly addressing the credit market.

This study diverges from the existing literature in two important ways. First, it focuses directly on the alternative credit market—a growing, non-bank source of finance often overlooked in financial stability research. Second, it integrates FinTech and BigTech credit to assess their evolving relationship with financial stability under external shocks. In doing so, this study offers one of the first comprehensive, cross-country assessments of the financial stability implications of alternative credit. This goes beyond narrow case studies focused on innovation trends or adoption indices, providing novel insights into the alternative credit–financial stability nexus, particularly during periods of economic stress.

The analysis uses a panel dataset of 1,024 observations from 145 countries between 2013 and 2020. First, employing a Two-Stage Least Squares (2SLS) method to address endogeneity, the study finds that alternative credit—including FinTech and BigTech credit—complements traditional bank credit. A 1% increase in FinTech credit is associated with a 0.054% rise in bank credit, while BigTech credit raises bank lending by 0.12 units per million USD. Although modest in magnitude, this complementarity likely reflects both partnerships that expand credit access and competitive pressures that drive banks toward operational efficiencies through digitization.

Second, external shocks such as the COVID-19 pandemic reduce the availability of bank credit, with results showing a consistent negative interaction between alternative credit and COVID-19. This indicates that the crisis attenuates the complementarity between digital and conventional credit, possibly due to heightened risk aversion, rising defaults, and disrupted data flows during the shock period.

Third, using a two-way fixed effects model with Z-scores as a financial stability measure, the study finds that alternative credit modestly enhances banking stability. Robustness checks using Half-Panel Jackknife Fixed Effects (HPJ-FE) and Group Fixed Effects (GFE) confirm these findings. FinTech credit demonstrates a stronger association with stability than BigTech credit, likely due to its lower interconnectedness and more targeted lending model. However, the stabilizing role of BigTech credit diminishes during periods of heightened systemic stress, such as the pandemic, reinforcing the context-dependent nature of these effects.

The remainder of this paper is organized as follows: Section 2 reviews the related literature. Section 3 presents data, empirical strategy, and methodology. Section 4 discusses the results, and Section 5 provides robustness checks and alternative approaches. Section 6 concludes and provides policy implications.

2 Literature Review

This paper relates to two main strands of literature. The first strand discusses how alternative bank credit compares to traditional bank credit and reviews prior studies on whether alternative credit serves as a substitute for or complements existing bank credit. The second strand examines the impact of alternative credit on financial stability.

2.1 Relationship Between Alternative and Conventional Credit

Alternative credit has emerged with the promise of enhancing financial inclusion by bridging the credit gap for consumers and businesses in the market (Bazarbash, 2019; Bazarbash & Beaton, 2020; Berg et al., 2020; Cornelli et al., 2020; Doerr, Gambacorta, et al., 2023; FSB & CGFS, 2017; Gambacorta et al., 2024; Jagtiani & Lemieux, 2019; Vuković et al., 2024). Alternative credit fosters more diversity in credit provision and efficiency pressures on incumbents. However, traditional banks may launch their platforms, acquire existing ones, or partner with FinTech platforms to prevent significant erosion of lending volume Hodula (2022) and Thakor (2020). This suggests that the relationship between alternative credit and conventional bank credit is not straightforward.

Often, the findings of the empirical studies yield mixed results. Bejar et al. (2022), Cole et al. (2019), Cornelli et al. (2022), Dolson and Jagtiani (2024), Jagtiani and Lemieux (2019), and Sheng (2021) found a complementary relationship between alternative and conventional bank credit.

Jagtiani and Lemieux (2019) showed that consumer lending activities have penetrated areas that may be underserved by traditional banks, such as in highly concentrated markets, areas with fewer bank branches per capita, and areas where the local economy is not performing well. FinTech firms have the potential to address information asymmetries. Sheng (2021) further supports this complementarity relationship between alternative and conventional bank credit by showing that FinTech improves banks' ability to extend credit to small and medium enterprises (SMEs) in China, mainly benefiting larger banks. The author argued that large banks could use FinTech to improve their lending technology by exploiting soft information obtained by FinTechs. Liberti and Petersen (2019) also showed that delegation of bank activities to FinTech avoids data collection and processing or real-time decision-making by humans, thereby reducing cost and error.

The complementarity relationship is explored from various perspectives and discussed in terms of the importance of financial inclusion through serving the unserved and reducing borrowing rates. To this effect, Cornelli et al. (2022) showed the potential FinTech lenders have in allowing small businesses that were less likely to receive credit through traditional lenders to access credit and to do so at a lower cost. Dolson and Jagtiani (2024) also showed that, for both personal loans and mortgage loans, FinTech lenders are more likely than other lenders (including both banks and other non-bank lenders) to reach out and offer credit to non-prime consumers. Jagtiani et al. (2021) found that mortgage loans are more likely to be originated by a FinTech lender in areas with a higher mortgage denial rate by traditional lenders in the previous period.

Hornuf et al. (2021) and Klus et al. (2019) further showed complementarity, even the presence of strategic alliance between firms that extends the alternative credit and conventional credit. Such partnerships could range from investing in small FinTechs to often building product-related collaborations with larger FinTechs. The alliance is stronger when banks pursue a well-defined digital strategy.

Hornuf et al. (2021) using hand-collected data covering the largest banks from Canada, France, Germany, and the United Kingdom, the authors showed the complementarity (even alliance) relationship between alternative credit and traditional bank credit. Klus et al. (2019) similarly showed the presence of strategic alliances between banks and FinTechs. The study showed that banks are particularly interested in benefiting from rapid innovation without necessarily being involved in its development, while FinTechs demand resources and know-how to scale in the highly regulated financial sector.

Cole et al. (2019) found that bank credit complements crowdfunding, including debt (marketplace lending), rewards, donations, and equity crowdfunding in the U.S. credit market. Cornelli et al. (2020) using cross-country analysis showed alternative credit complements traditional credit mainly in areas with fewer bank branches. Less stringent regulations, lower bank credit-to-deposit ratio, and advanced investor protection disclosure are also other factors that improve the extent of alternative credit.

Bejar et al. (2022) studied a limited sample of banks in Latin America and documented that banks in countries with a higher FinTech presence experience reduced interest income, highlighting the alternative markets' ability to challenge the existing bank practices and pose competitive pressure on banks. L. Fang et al. (2023) and Lee et al. (2021) analyzed whether FinTech innovation contributes to a bank's efficiency and mitigates bank risk in China. The study unveiled that FinTech innovation significantly improves banks' efficiency in profit, cost, interest, and non-interest income and overall bank performance.

On the contrary, de Roure et al. (2021) for Germany, Cornaggia et al. (2018) and Tang (2019) for the US, Phan et al. (2020) for Indonesia showed the presence of a substitutional relationship between alternative and conventional credit.

de Roure et al. (2021) presented a theoretical model and showed that P2P lending in Germany substitutes the banking sector for high-risk consumer loans. Their study further indicated that the P2P market draws risky and less profitable clients from traditional banks, highlighting positive social welfare implications. Cornaggia et al. (2018) document that about a quarter of small (rural) commercial banks in the U.S. consumer credit market lose lending volume to encroachment by P2P lending.

Using a panel of 41 banks in Indonesia Phan et al. (2020) showed that FinTech growth poses a threat to the performance of banks. Net interest income to total assets, return on equity and assets, and yield on earning assets declined following FinTech credit penetration. Likewise, a study by Naceur et al. (2023) shows that FinTech credit negatively affects banks' profitability, mainly by reducing interest income and increasing operational costs.

Other studies found both complementary and substitutionary relationships between alternative and conventional bank credit depending on several factors such as the size of the economy (Doerr et al., 2024; Kowalewski & Pisany, 2022), firm size, borrowers' quality (Tang, 2019), and bank characteristics (Hodula, 2022).

FinTech-based firms and BigTechs provide payment services complementary to the ones offered by banks in emerging economies and a substitute that competes with the payment services provided by banks in advanced economies (Doerr et al., 2024). Leveraging a database of bank-level and country-level characteristics for 72 countries from 2013 to 2018, Kowalewski and Pisany (2022) find that FinTechs play a complementary role to traditional credit in emerging economies, while tech companies compete with and push some banking exit out of the market, both in emerging and developed economies.

Using the data from the Lending Club and regulatory reform in 2010 as a negative bank credit supply shock Tang (2019) demonstrates that P2P lending is a substitute for bank lending in terms of serving infra-marginal bank borrowers but complements bank lending to small loans in the US consumer credit market.

Gambacorta et al. (2022) examined the competition between BigTechs and banks in the loan market for SMEs, where adverse selection and difficulty in enforcing repayment cause friction. A default on a BigTech loan may lead to the exclusion of the firm from future loans, as in the case of bank lending and the exclusion from the BigTechs' platform.

A cross-country study by Hodula (2022) showed that FinTech credit platforms can act as both complements and substitutes for traditional bank credit depending on the banking sector's characteristics. In less concentrated and more stable banking sectors, they tend not to compete for the same clientele and coexist as complements and vice versa.

2.2 Impact of Alternative Credit on the Financial Stability

The relationship between competition and financial stability remains a foundational debate in financial economics, broadly characterized by two opposing schools of thought. The competition-stability view holds that increased contestability—whether through actual entry or reduced barriers—promotes efficiency, lowers costs, and reduces the dominance of "too-big-to-fail" institutions, thereby mitigating systemic risk and moral hazard (Amidu & Wolfe, 2013; BIS, 2019; Feldman & Schmidt, 2001; Feyen et al., 2021). Empirical work by Noman et al. (2017) supports this, demonstrating that moderate competition (measured via the Panzar-Rosse H-statistic) strengthens ASEAN banks' Z-scores and lowers non-performing loans. Competition is also seen as a catalyst for innovation, improved customer service, and financial inclusion by reducing incumbents' ability to extract rents and compelling them to diversify their offerings (Čihák et al., 2021).

In contrast, the competition-fragility view argues that excessive competition erodes profit margins and franchise value, potentially triggering excessive risk-taking among financial institutions. More profitable banks are often more stable—they can afford to build capital buffers and maintain prudence (Hellmann et al., 2000; Martynova et al., 2020). Banks in highly concentrated markets tend to have more stable and insured funding sources, although this can also invite moral hazard. During rapid market transitions, new entrants may cherry-pick high-margin clients, leaving incumbents with riskier segments (Feyen et al., 2021).

Digital transformation complicates this dynamic by altering how competition operates in practice. While FinTech and BigTech firms initially enhance contestability, their long-term effect may be reduced competition due to data advantages, platform control, and self-reinforcing network externalities called the DNA feedback loop (BIS, 2019; Feyen et al., 2021; Ong & Toh, 2023). BigTechs can leverage their dominance in non-financial platforms (eg, e-commerce or search engines) to bundle services, collect behavioral data, and entrench market share. These firms may also create conflicts of interest by serving both as competitors and infrastructure providers for banks, distorting the competitive landscape (Ong & Toh, 2023). Over time, such dynamics may reduce long-term contestability, particularly in weakly regulated markets, undermining systemic resilience (Khattak et al., 2023).

The nexus between financial inclusion and stability is similarly nuanced and nonlinear. Broader access to credit and savings can diversify risk pools and integrate informal sectors, enhancing systemic resilience. Čihák et al. (2021) showed that inclusive policies significantly reduce poverty-related default rates when paired with financial literacy programs. Likewise, Jungo et al. (2022) found that in Sub-Saharan Africa and Latin America, inclusion reduced credit risk by 12% under strong regulatory environments. However, unregulated financial inclusion can backfire. In Kenya, aggressive microlending led to a 34% increase in household debt-to-income ratios, amplifying systemic vulnerabilities. These outcomes demonstrate that inclusion is not inherently stabilizing but depends on institutional safeguards and consumer protection.

Diversification as a competitive strategy and a digital transformation outcome introduces additional complexity to financial stability. The relationship is nonlinear. Kim et al. (2020) identified an inverted U-shaped curve where moderate diversification stabilizes earnings, but excessive reliance on non-traditional income increases fragility during crises. For example, OECD banks deriving over 30% of income from non-interest sources experienced greater instability during the 2008 financial crisis. Khattak et al. (2023) extended this logic to digital diversification, finding that banks adopting complex digital models without parallel upgrades in risk governance become more vulnerable. As financial institutions expand into data monetization, embedded finance, or third-party platforms, the stabilizing potential of diversification hinges on institutional capacity, supervisory oversight, and digital risk management (Syed et al., 2021).

Prior empirical studies on FinTech and BigTech credit's impact on financial stability have faced data limitations in assessing market penetration, credit expansion, and systemic risks. Nevertheless, contributions by Carstens et al. (2021), Cheng and Qu (2020), Daud et al. (2022), Elekdag et al. (2024), Gambacorta et al. (2024), Philippon (2016, 2019), and Vuković et al. (2024) offer valuable insights.

Philippon (2016) theoretically discussed the potential impact of FinTech on the finance industry, focusing on financial stability and access to services. The study argued that innovations by FinTechs can democratize access to services and foster entrepreneurship while also introducing privacy and regulatory challenges. The study highlights inefficiencies in the current financial system, as evidenced by stagnant financial intermediation costs for over two centuries. BIS (2019) and Carstens (2018) highlights the systemic risk posed by online Money Market Funds (MMFs) as they could be subject to investor runs in the event of credit or duration losses.

Gambacorta et al. (2024) showed that alternative credit platforms, leveraging alternative data and effectively analyzing the collected data through AI and machine learning, outperform traditional models in predicting defaults, particularly during credit supply shocks. The non-traditional alternative data source could range from social media activity (Q. Fang et al., 2015; Jagtiani & Lemieux, 2019), digital footprints (Berg et al., 2020), transaction history, and customer reviews (Feng et al., 2021; Frost et al., 2019). This highlights alternative credit's role in enhancing financial inclusion and stability.

Similarly, studies by Daud et al. (2022), Elekdag et al. (2024), and Fung et al. (2020) examine the impact of FinTech on financial stability across different markets, with findings suggesting that FinTech can either mitigate or increase financial institutions' fragility depending on market characteristics, institutional strength, and the level of bank concentration. The studies found that FinTech increases competition, impacting banks' risk-taking behavior, and strong domestic institutions and bank concentration can complement FinTech's positive effects on financial stability.

The relationship between FinTech and financial stability varies across markets. Cheng and Qu (2020) and Fung et al. (2020) find that FinTech innovations have differing impacts depending on market characteristics, reducing financial institutions' fragility in emerging economies while increasing it in developed markets. Additionally, Vuković et al. (2024) using a monthly dataset from 2015 to 2022 and applying a robust Global Vector Autoregressive (GVAR) model to study the BRICS economies, it is concluded that FinTech does not significantly threaten financial stability in the short term.

Daud et al. (2022) investigates the relationship between FinTech and countries' financial stability in a panel of 63 countries from 2006 to 2017. By employing the dynamic panel of the System Generalized Method of Moments (GMM) estimator, they find that FinTech promotes financial stability through the channels of artificial intelligence, cloud technology, and data technology. Using a panel of banks from 84 countries and treating the introduction of FinTech regulatory sandboxes as an exogenous shock, Fung et al. (2020) showed FinTech reduces financial institutions' fragility in emerging economies but increases it in developed markets when market and bank characteristics are accounted for. Khan et al. (2023) also used the Fintech adoption index and regulatory sandbox to investigate the effect of FinTech development on banking sector stability. Focusing on GCC countries and using data from 2010 to 2022, Khan et al. (2023) found that FinTech adoption negatively affects banks' stability. Thus, findings on the effects of FinTech adoption on banks' stability are empirically contested. However, these studies were focused on the impact of technology adoption, such as artificial intelligence, cloud technology, and data technology, on financial stability.

3 Data, Empirical Framework and Methodology

This section first outlines the main variables and data sources used in the analysis. It then presents key stylized facts and introduces the empirical strategy for estimating the effects of alternative credit on both traditional bank lending and financial stability. Finally, it discusses alternative model specifications and robustness checks.

3.1 Data and Variable Description

The empirical analysis relies on a balanced panel dataset comprising 145 countries observed annually from 2013 to 2020. The first dependent variable is traditional bank credit, which measures the total volume of domestic credit extended by banks to the private sector. This is expressed in constant U.S. dollars and transformed into natural logarithms to reduce skewness. The data are sourced from the World Bank's World Development Indicators (WDI).

The second dependent variable is financial stability, proxied by the country-level Z-score, a widely adopted indicator in the literature for measuring a banking system's distance to insolvency (Beck et al., 2013; Fung et al., 2020; Houston et al., 2010; Laeven & Levine, 2009). The Z-score is calculated as $(\text{ROA} + \text{CAR})/\sigma(\text{ROA})$, where ROA denotes return on assets, CAR is the capital-asset ratio, and $\sigma(\text{ROA})$ represents the standard deviation of ROA over a five-year rolling window. A higher Z-score indicates greater financial stability, while lower values reflect increased fragility and vulnerability to shocks. Data on Z-scores are retrieved from the Global Financial Development Database (GFDD).

One of the primary independent variables of interest is *alternative credit*, defined as credit provided by non-traditional financial intermediaries and measured as the combined volume of FinTech and BigTech lending. These credit volumes are expressed in U.S. dollars per capita. FinTech credit includes digital lending models such as peer-to-peer (P2P) lending, invoice trading, and other debt-based financing mechanisms facilitated through online platforms (CCAF, 2021; Claessens et al., 2018; Wardrop et al., 2015). Data on FinTech credit are sourced from the Global Alternative Finance Database, maintained by the Cambridge Centre for Alternative Finance (CCAF). This dataset is compiled using a combination of industry surveys, web scraping, and collaboration with research and academic institutions. BigTech credit refers to lending by large technology firms—such as Ant Financial, Tencent, Amazon, and M-Pesa—whose primary business activities lie outside the financial sector but increasingly engage in financial intermediation, either directly or through partnerships with regulated financial institutions. BigTech credit data are obtained from Cornelli et al. (2023) and Frost et al. (2019), who compile lending figures from publicly available sources, regulatory filings, and firm-level disclosures. Whereas FinTech credit typically involves technology-enabled non-bank financial institutions, BigTech credit is embedded within broader digital ecosystems where financial services complement core platform-based offerings. Together, FinTech and BigTech credit comprise the alternative credit market, which operates largely outside the traditional banking system.

To control for confounding factors, the analysis includes a set of covariates grouped into macroeconomic, financial, and institutional/technological dimensions. The selection of these variables follows established studies on the determinants of credit market development and financial stability, including Carstens (2018), Doerr, Gambacorta, et al. (2023), Frost et al. (2019), and Hodula (2022), and is grounded in both theoretical relevance and empirical precedent. Macroeconomic controls include GDP per capita and its squared term (to account for non-linearities), inflation (based on annual changes in the consumer price index), trade openness (trade-to-GDP ratio), and short-term real interest rates. These variables capture country-specific macroeconomic conditions that shape credit demand and supply.

Banking sector indicators include the non-performing loans (NPL) ratio, net interest margin, return on assets (ROA), liquidity, and the bank concentration ratio—each reflecting profitability, credit risk, and structural competitiveness within the financial sector. Institutional and technological dimensions are proxied by the Lerner index (for market power), bank branch density (for financial outreach), regulatory stringency (capturing the intensity of prudential frameworks), public trust in technology firms (relevant for FinTech/BigTech uptake), and digital infrastructure (mobile and broadband penetration per 100 inhabitants).

Monetary variables are primarily log-transformed to mitigate skewness and facilitate elasticity-based interpretations. However, level specifications are also tested in robustness checks. All control variables are lagged by one year to reduce simultaneity bias and address endogeneity concerns. Data on such controls are obtained from various sources such as the WDI and the Global Financial Development Database (GFDD). Descriptions and sources of the control variables are provided in Table A1.

To account for the economic disruptions caused by the COVID-19 pandemic, the study includes variables capturing the severity of the pandemic in each country-year. These are drawn from Mathieu et al. (2020) and the Oxford COVID-19 Government Response Tracker (OxCGRT) developed by Hale et al. (2021). Indicators such as new confirmed COVID-19 cases per capita, hospitalization rates per 1,000 population, and COVID-related death rates are used, in line with approaches adopted in Ng (2021).

3.2 Descriptive Statistics and Stylized Facts

This subsection outlines key patterns and trends in alternative credit, financial stability, and credit market structure, drawing on both summary statistics and visual evidence.

The volume of credit extended by FinTech providers varies significantly across countries. In 2017, China accounted for the largest share globally, with USD 357 billion in FinTech lending, followed by the United States with USD 71.6 billion. Across the countries included in this study, the average annual FinTech lending volume per country stood at USD 1.43 billion. China also led in BigTech credit, reaching USD 669 billion in 2020. By contrast, the average annual lending by BigTech firms across all sampled countries is USD 2.87 billion, while the total average for combined alternative credit reached approximately USD 3.41 billion. Descriptive statistics for all key variables are provided in Table A2.

Additional insights emerge from graphical representations of the geographic spread of alternative credit. The global evolution of alternative credit between 2013 and 2020 illustrates a notable shift from a regionally concentrated activity to a more widely diffused financial innovation. As shown in Figure 1.1, the sector was still in its early stages in 2013, with substantial activity concentrated in a few countries, including China, the United States, and the United Kingdom. In contrast, many other regions, particularly Sub-Saharan Africa, the Middle East, and South America, displayed minimal or no observable activity.

By 2020, however, the geographic footprint of alternative credit had expanded significantly, as illustrated in Figure 1.2. Emerging economies such as Kenya, India, and Indonesia experienced substantial growth, enabled mainly by mobile-first financial strategies and the proliferation of digital wallets such as M-Pesa and Paytm, allowing for rapid credit delivery without traditional banking infrastructure. Similarly, several countries in Latin America exhibited increasing adoption, highlighting the role of technology-enabled credit in promoting financial inclusion. Nevertheless, the 2020 landscape continues to show disparities: regions affected by conflict or constrained by underdeveloped digital infrastructure still lag in adoption rates. Overall, these patterns underscore both the accelerated global diffusion of alternative credit and the persistent heterogeneity in its adoption across countries and regions.

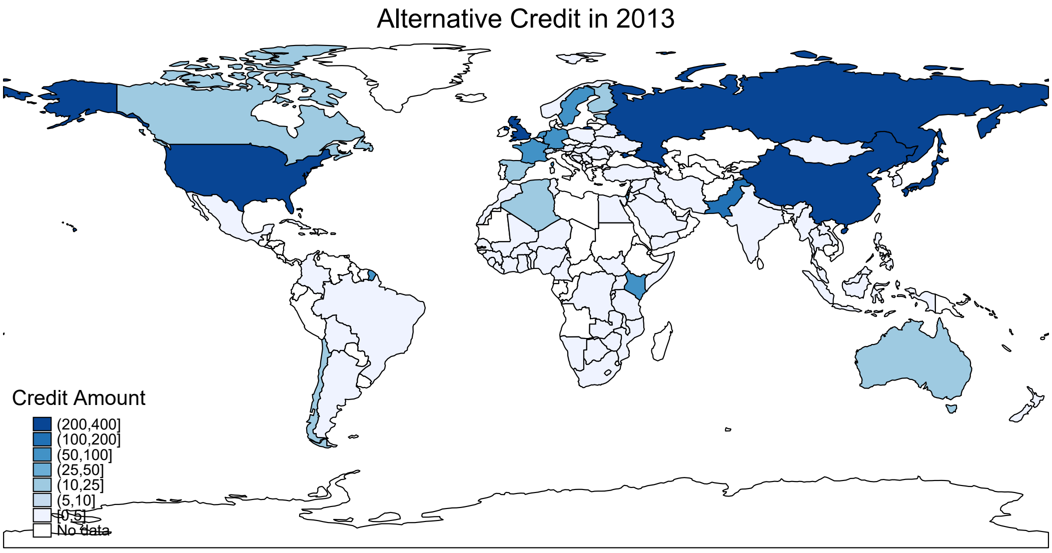

Figure 1.1: Global Alternative Credit Distribution in 2013 .

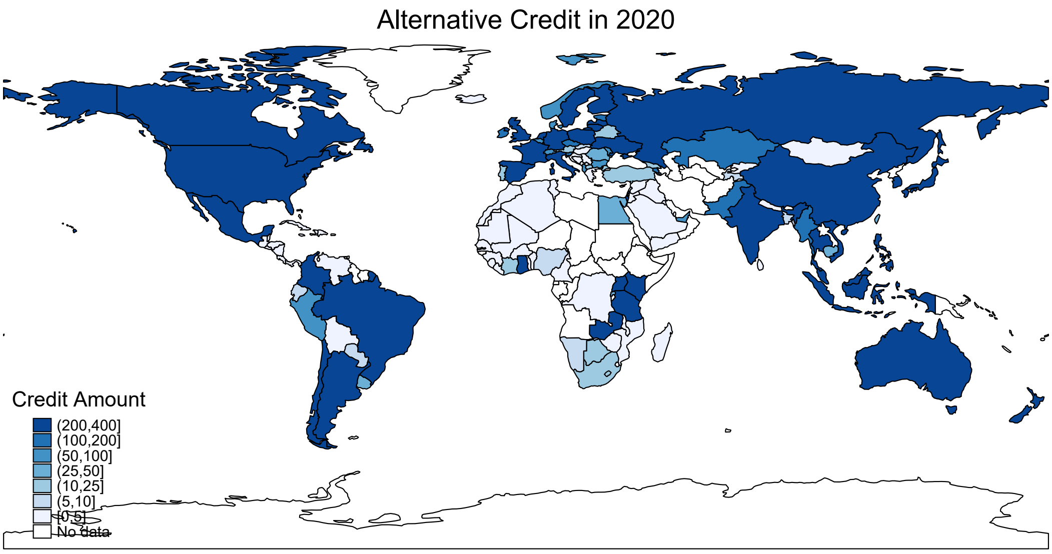

Figure 1.2: Global Alternative Credit Distribution in 2020 .

Figure 1.3 depicts the evolution of FinTech, BigTech, and overall alternative credit volumes between 2012 and 2020. The graph shows a sustained upward trend in BigTech and alternative credit, particularly between 2015 and 2019. In contrast, FinTech credit demonstrates rapid initial growth, peaking around 2017–2018, followed by a noticeable decline or plateau thereafter, as a wave of platform-level defaults, regulatory interventions, and market exits began to weigh on the sector's expansion trajectory (Cornelli et al., 2020). This pattern suggests that FinTech credit was the dominant form of non-bank lending in the early phase of digital credit expansion, especially in countries with established peer-to-peer platforms and advanced digital infrastructure.

However, beginning in 2016, BigTech credit exhibits accelerated growth, consistent with the expansion of platform-based ecosystems and the integration of financial services into broader digital business models. This trajectory reflects the influence of the Data-Network-Activity (DNA) feedback loop described by Frost et al. (2019), in which increased user activity and data generation reinforce platform scalability. The eventual overtaking of FinTech by BigTech in terms of credit volume highlights a structural shift in the alternative credit landscape and the growing systemic relevance of large technology firms in financial intermediation.

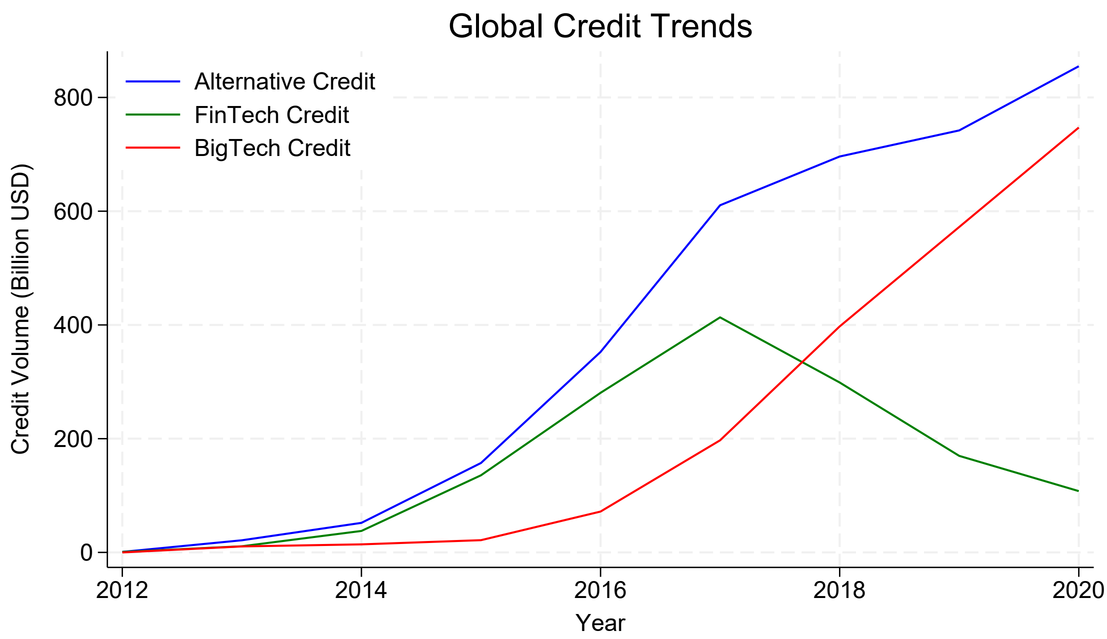

Figure 1.3: Trends in Alternative, FinTech and BigTech Credit

Figure 1.4 displays the annual volumes of FinTech and BigTech credit in a stacked bar format, illustrating their relative contributions to total alternative credit over time. In line with earlier observations, FinTech dominated the initial phase of growth; however, BigTech experienced accelerated expansion during the latter half of the decade. This transition highlights the increasing significance of platform-based ecosystems and large technology firms in the evolution of credit markets. The rising share of BigTech credit may reflect its structural advantages, including integration of financial services with broader digital offerings and privileged access to granular consumer data. Notably, global FinTech credit volumes declined since 2018, driven primarily by regulatory tightening and market disruptions in China, despite continued growth in other regions (Cornelli et al., 2020). Meanwhile, investor returns in FinTech lending have diminished over time, whereas BigTech firms continue to report high profit margins in their core platform businesses.

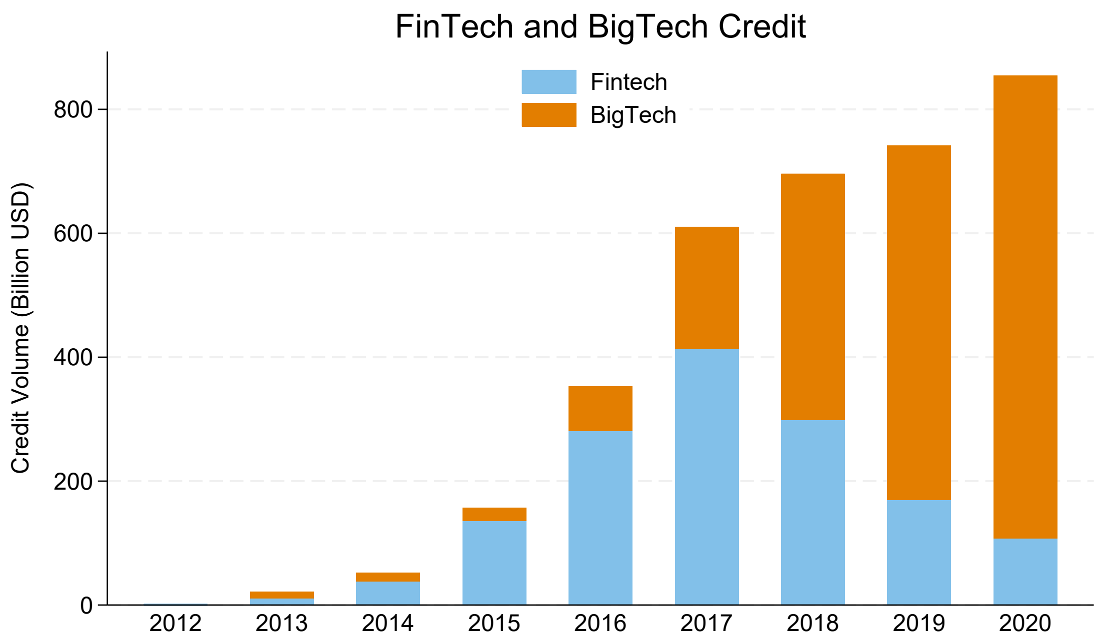

Figure 1.4: Evolution of FinTech and BigTech Credit ·

Figure 1.5 offers a disaggregated comparison of the top 20 countries by the logarithmic value of credit volume for alternative, FinTech, and BigTech credit. The figure reinforces the dominance of China across all three credit modalities, followed by the United States and Japan. This aligns with prior literature indicating China's robust shadow banking activity, widespread platform finance, and state-enabled data ecosystems that favor non-bank credit expansion (Cornelli et al., 2020; Doerr, Gambacorta, et al., 2023). Interestingly, Kenya ranks among global leaders in BigTech lending, reflecting their successful mobile-first financial inclusion strategies. Other emerging economies such as Vietnam and Brazil also show relatively high levels of alternative credit, indicating broader inclusion outside traditional bank channels.

The combination of these figures paints a dynamic picture: alternative credit has grown in volume and diversified geographically and institutionally. While early expansion was

FinTech-driven and regionally concentrated, recent trends highlight the rapid scaling of BigTech in both advanced and emerging markets.

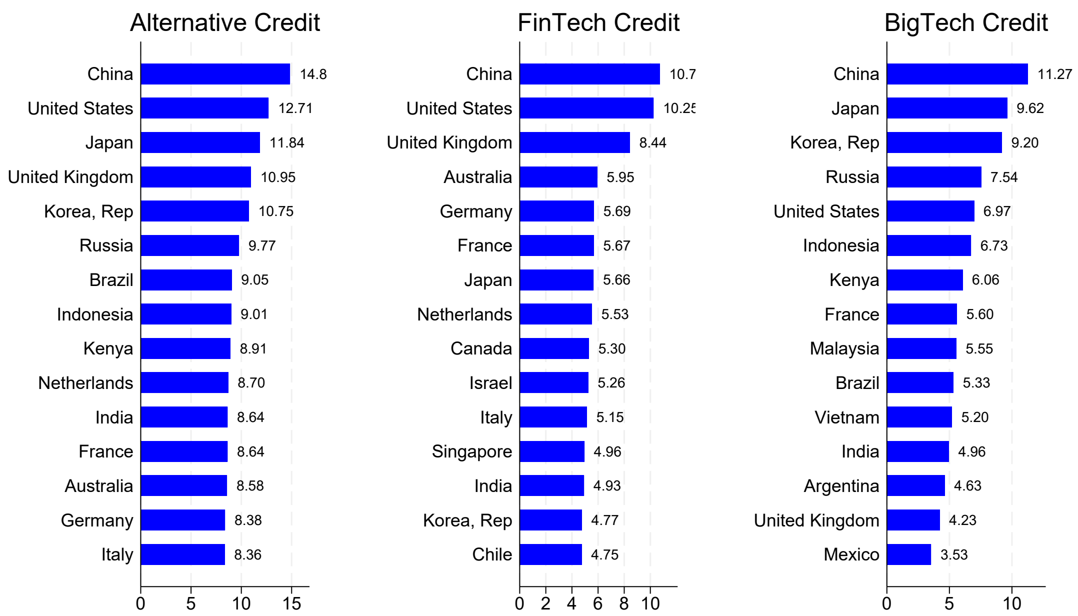

Figure 1.5: Leading countries in Alternative, FinTech, and BigTech Credit

Figure 1.6 provides a two-panel view of domestic credit trends. Panel (a) ranks countries by the absolute volume of domestic credit, measured in billion USD. It highlights the dominance of large and financially mature economies, most notably China, the United States, and the United Kingdom. These countries maintain deep financial systems and are among the most active in expanding alternative credit markets. Despite these high volumes, panel (b)—which plots total domestic credit as a percentage of GDP over time—reveals a more nuanced picture. The ratio appears relatively stable or even slightly declining in several major markets, suggesting that domestic credit growth has not significantly outpaced GDP expansion.

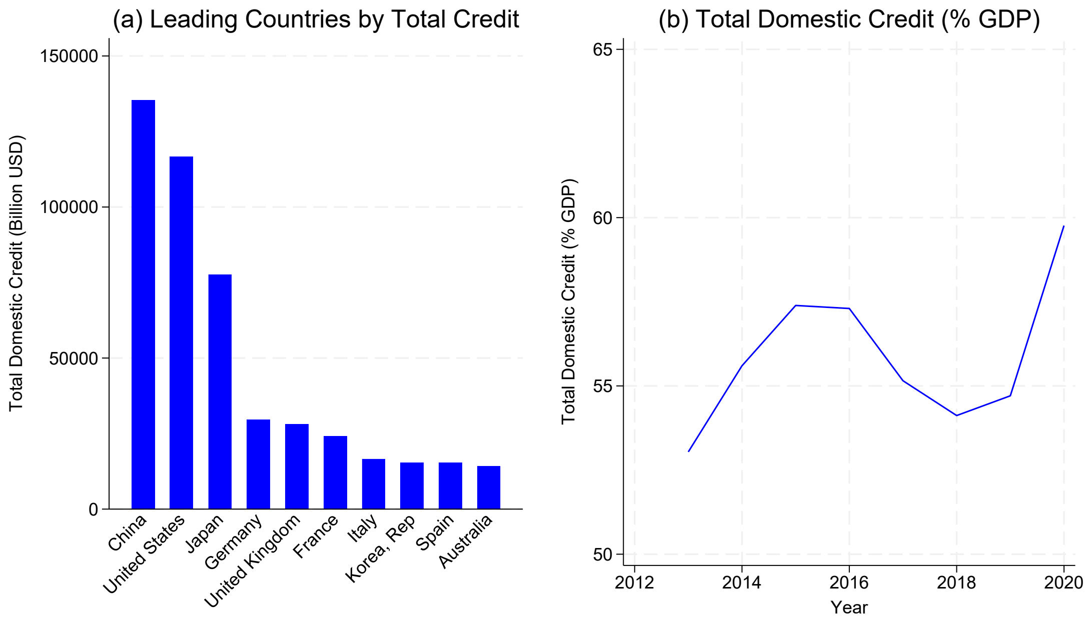

Figure 1.6: Leading Countries by Total Credit(a) and (b) Total Domestic Credit (% GDP)

Figure 1.7 juxtaposes the absolute volumes of alternative credit with its share relative to total domestic credit, offering a more nuanced assessment of its systemic role. While large economies such as China, the United States, and the United Kingdom dominate in absolute volume, adjusting for total credit reveals a different pattern. The relative share of alternative credit is higher in lower-income economies, where it often addresses gaps left by traditional banking systems. Among the leading countries, China and Kenya report alternative credit flows exceeding 1% of total domestic credit stocks, signaling meaningful integration into their broader financial ecosystems. By contrast, major economies like the United States, Japan, the United Kingdom, and Korea exhibit lower relative shares—typically below 1%—despite their high financial sector depth. Although its overall share is still limited, the upward trend underscores its growing relevance, consistent with the evidence presented by Cornelli et al. (2020) and FSB and CGFS (2017).

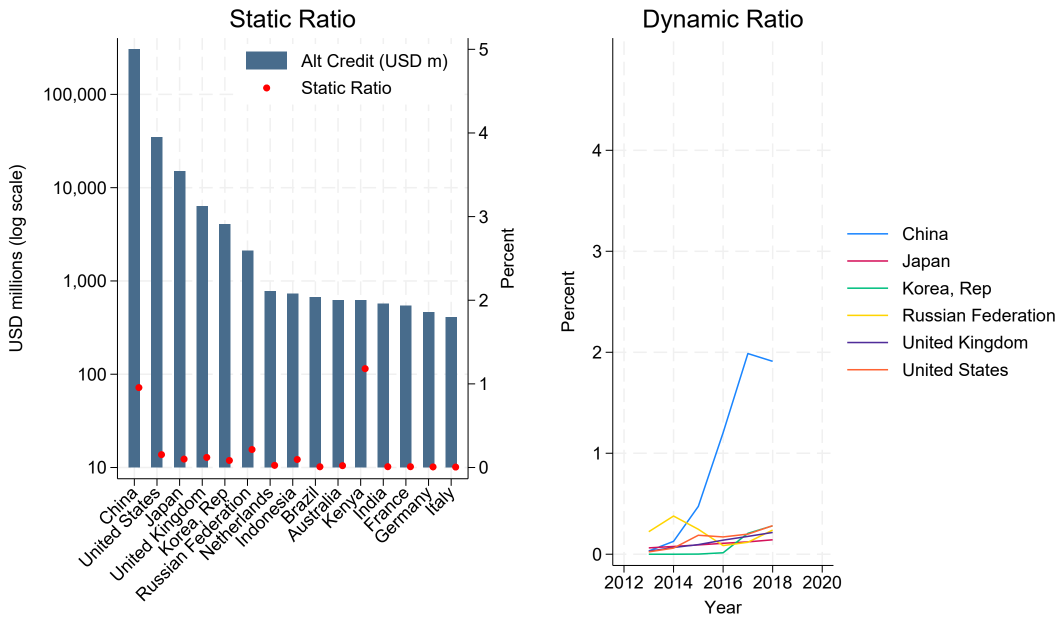

Figure 1.7: Static and Dynamic Ratio of Alternative Credit to Total Credit ·
Static ratio applied on the year 2020.

Figure 1.8 presents the global trend in Z-scores—a proxy for financial stability—over the period 2012 to 2020. Higher values indicate a greater distance from insolvency, signifying a more stable banking system. From 2012 to 2019, the Z-score rose gradually, likely reflecting post-crisis regulatory reforms and favorable macroeconomic conditions. However, the trend reverses thereafter, with a noticeable decline coinciding with the onset of the COVID-19 pandemic.

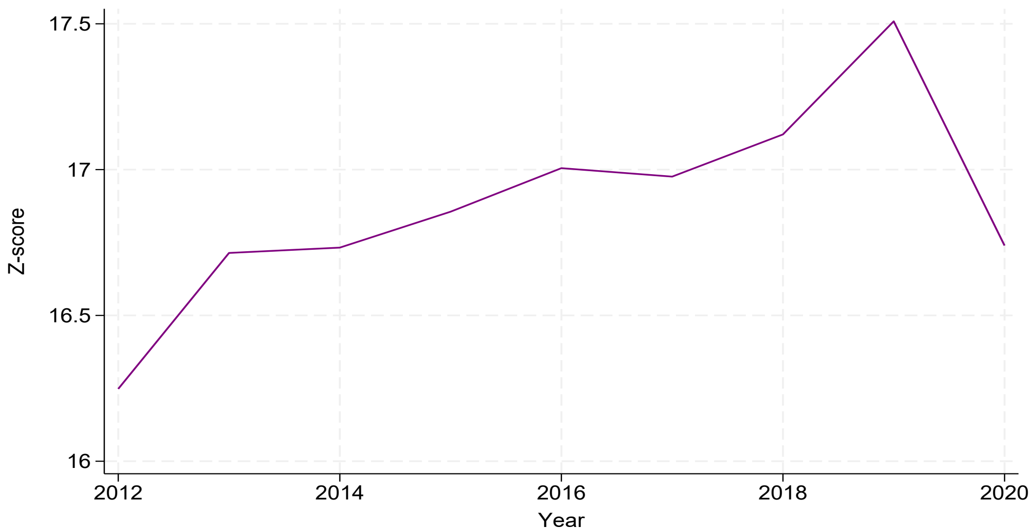

Figure 1.8: Mean Z-score (Financial Stability) ·

3.3 Empirical Strategy

This study empirically examines two core relationships. First, it investigates the influence of alternative credit—comprising FinTech and BigTech lending—on the supply of traditional bank credit. Second, it evaluates the impact of alternative credit on financial stability, proxied by the Z-score. Both analyses are conducted using a panel fixed-effects framework with annual data covering 145 countries over the period 2013–2020.

However, this investigation presents complex identification challenges. The rapid growth of FinTech and BigTech platforms has prompted strategic responses from incumbent banks, such as developing proprietary digital platforms, acquisitions of alternative lenders, and collaborative ventures (Hodula, 2022; Thakor, 2020). These strategic responses introduce simultaneity and potential reverse causality between traditional and alternative credit, leading to endogeneity concerns. For instance, increased FinTech activity may influence banks' risk strategies. Although fixed effects help address time-invariant heterogeneity, they do not eliminate endogeneity arising from simultaneity or omitted variable bias.

To mitigate these concerns, I employ a two-stage least squares (2SLS) instrumental variables (IV) approach, consistent with prior research examining the macro-financial effects of innovation (Arner et al., 2015; Cheng & Qu, 2020; Hodula, 2022; Roberts & Whited, 2013). Despite the challenge of identifying instruments that satisfy both the relevance and exogeneity conditions, recent studies have employed digital infrastructure indicators as effective proxies for FinTech and broader financial innovation. Specifically, Cornelli et al. (2020), Cuadros-Solas et al. (2024), Haddad and Hornuf (2019), and Hodula (2022) use mobile phone subscriptions and fixed broadband penetration as instrumental variables for alternative credit.

These variables represent foundational infrastructure required for developing and diffusing digital lending platforms, particularly in enabling access to and use of FinTech and BigTech services. These technologies facilitate remote identity verification, algorithmic credit scoring, and app-based loan disbursement—core components of digital lending ecosystems. Mobile networks support SMS- and app-based lending services, while broadband enables seamless access to online and platform-integrated lending channels. Empirical evidence confirms their relevance: Cuadros-Solas et al. (2024) demonstrate a robust positive association between mobile penetration and FinTech credit volumes across countries, and Emara and Mohieldin (2023) show that both mobile and broadband access strongly predict financial inclusion through a FinTech readiness index, indicating that digital infrastructure enables and actively drives alternative credit.

While such infrastructure may co-evolve with economic growth, it is primarily shaped by long-term technological adoption and policy-driven investment rather than short-term fluctuations in credit supply. Importantly, after conditioning on macro-financial controls and fixed effects, these infrastructure indicators are plausibly exogenous to short-term variation in traditional bank credit and financial stability (D'Andrea et al., 2023; Selim Elekdag, 2024). In the short term, their evolution is largely governed by structural factors—such as regulatory environments, national development strategies, spectrum allocation, and public or private telecom investment—which unfold over multi-year horizons and are unlikely to respond to year-on-year changes in credit supply or banking sector soundness. As such, mobile and broadband penetration are plausibly orthogonal to contemporaneous bank credit dynamics.

To reinforce the credibility of the identification strategy, this study implements three key measures. First, the model includes a comprehensive set of macroeconomic and banking sector controls—such as GDP per capita, bank branch density, regulatory quality, and market structure indicators. Second, all control variables are lagged by one year to mitigate simultaneity bias, and both country and year fixed effects are added to absorb time-varying shocks and unobserved heterogeneity. Third, the study assesses instrument strength using first-stage F-statistics and tests exclusion validity through Hansen's overidentification J-test. In addition, I employ alternative estimators—such as half-panel jackknife fixed effects and grouped fixed-effects models—to verify the robustness and consistency of the baseline results.

Following Cornelli et al. (2020) and Hodula (2022), the baseline specification is a conventional two-stage least squares panel estimator, where the following is the first-stage equation.

$$AC_{it} = \alpha + \beta_1 Mob_{it} + \beta_2 BI_{it} + \gamma X_{i,t-1} + \theta_t + \phi G_i + \epsilon_{it} \tag{1.1}$$

where, AC_{it} is the volume of FinTech, BigTech, or total alternative credit per capita in country i and year t; Mob_{it} and BI_{it} represent mobile phone and fixed broadband subscriptions, respectively. The control vector $X_{i,t-1}$ is selected following the works of

Carstens (2018), Doerr, Gambacorta, et al. (2023), Frost et al. (2019), and Hodula (2022) and includes lagged GDP per capita (and its square), the Lerner index, bank branches, regulatory stringency index, and an index for customers' trust in technology firms. θ_t captures year-fixed effect, G_i accounts for country-fixed effect, and ϵ_{it} is country-specific idiosyncratic shocks at year t, which is assumed to be well-behaved.

To estimate the impact of alternative credit on conventional bank credit, I use the following second-stage IV regression equation, which takes the fitted value, $\widehat{AC_{it}}$, from Equation 1.1 as a control and is given by:

$$TBC_{it} = \alpha + \psi \widehat{AC_{it}} + \gamma X_{i,t-1} + \delta Covid_{it} + \theta_t + \phi G_i + \epsilon_{it} \tag{1.2}$$

where, TBC_{it} is the per capita volume of traditional bank credit. The control vector $X_{i,t-1}$ includes inflation, interest rates, trade openness, GDP per capita (and its square), Covid-19, capital adequacy, return on assets, liquidity, bank concentration, branch density, population growth, and regulatory stringency. All continuous variables are in natural logarithms except for indices, dummies, and inflation. $Covid_{it}$ captured by hospitalization rates, new confirmed cases, COVID-related death rates, and a composite Stringency Index on government response. θ_t captures year-fixed effect, G_i accounts for country-fixed effect, and ϵ_{it} is country-specific idiosyncratic shocks at year t, which is assumed to be well-behaved.

To estimate the impact of alternative credit on financial stability, I employ a fixed effects model, following the empirical frameworks of Cheng and Qu (2020), Cuadros-Solas et al. (2023), Daud et al. (2022), and Fung et al. (2020).

$$FS_{it} = \alpha + \psi AC_{it-1} + \gamma X_{i,t-1} + \theta_t + \phi G_{it} + \epsilon_{it} \tag{1.3}$$

where, the dependent variable FS_{it} is financial stability as measured by the country-level bank Z-score, and AC_{it-1} is the lagged alternative, FinTech and BigTech credit per capita. $X_{i,t-1}$ is a vector of control variables that includes GDP per capita (and its quadratic form), trade openness, inflation, domestic credit to the private sector as percentage of GDP, Lerner index of banking sector mark−ups, regulatory stringency index, provision of non-performing loan rate, net interest margin, and bank concentration ratio. G_{it} is a vector of geographical region fixed effects, θ_t is year fixed effect, and ϵ_{it} is the idiosyncratic error term. The regressors are lagged by one year to mitigate endogeneity issues. All variables other than the dummies, indices, and inflation rate are natural log transformations.

A potential concern in this analysis is the endogeneity of alternative credit, which may be jointly determined with financial stability. As noted by Cheng and Qu (2020), financial innovation and financial stability often evolve in tandem, raising concerns about reverse causality and omitted variable bias. To address this, I adopt an instrumental variables (IV) approach, consistent with prior studies (Arner et al., 2015; Cheng & Qu, 2020; Cornelli et al., 2020; Hodula, 2022; Roberts & Whited, 2013) and use the established instruments, mobile phone penetration and fixed broadband subscriptions as instruments for alternative credit.

In the first stage of the two-stage least squares (2SLS) estimation, alternative credit is regressed on mobile and broadband penetration, alongside other exogenous controls, as specified in Equation 1.1. The second-stage regression then estimates the effect of instrumented alternative credit on financial stability and is given by:

$$FS_{it} = \alpha + \psi \widehat{AC_{it}} + \gamma X_{i,t-1} + \theta_t + \phi G_i + \epsilon_{it} \tag{1.4}$$

where, FS_{it} is financial stability, measured by the country-level bank Z-score for country i, at year t. $\widehat{AC_{it}}$ is a fitted value of alternative credit (including FinTech credit and BigTech credit) obtained from the first-stage regression. The vector of controls $X_{i,t-1}$ remains consistent with the baseline specification in Equation 1.3.

To capture the impact of external shocks, such as COVID-19 and the GDPR regulatory change, on bank credit via alternative credit, I incorporate interactions between alternative credit and both COVID-19 and GDPR into Equation 1.2. I analyze three variations of this Equation: first, I look at the effects of alternative credits in relation to COVID-19 and the GDPR regulatory shock individually, and then I consider both shocks simultaneously. A negative coefficient of these interactions suggests that the presence of these shocks dampens the effect of alternative credit on bank credit. For instance, a negative coefficient for the interaction between COVID-19 and alternative credit indicates that, during the pandemic, the effect of alternative credit on the supply of bank credit is diminished compared to times before the outbreak.

To assess the moderating effect of the COVID-19 shock on financial stability, I introduce an interaction between the fitted value of alternative credit and the COVID-19 indicator into Equations 1.3 and 1.4. A negative coefficient on the interaction term would suggest that the pandemic weakened the influence of alternative credit on financial stability, likely due to pandemic-related economic disruptions and market stress.

3.4 Alternative Approach and Robustness Checks

While the primary estimation strategy employs a two-stage least squares panel model with fixed effects to estimate the impact of alternative credit on both traditional bank credit and financial stability, additional approaches are considered to strengthen the empirical analysis. The fixed-effects 2SLS framework offers a solid basis for addressing time-invariant unobserved heterogeneity and endogeneity concerns through external instruments. However, two further dimensions merit exploration to ensure the robustness and depth of the results. First, the possibility of persistent dynamics or inertia in financial variables suggests that a dynamic specification may offer a more complete representation of the underlying processes. This is mainly because traditional bank credit evolves gradually due to prior lending commitments, regulatory cycles, and institutional persistence. Likewise, financial stability reflects slow-moving balance sheet dynamics and risk accumulation. Second, the broad cross-sectional dimension of the dataset covering 145 countries may warrant a cross-country difference in financial sector development, regulatory regimes, and digital infrastructure that may lead to variation in how countries respond to alternative credit, which a standard fixed-effects model may not fully accommodate.

To account for these considerations, this study implements two complementary approaches as robustness checks: the half-panel jackknife fixed-effects (HPJ-FE) estimator to address potential bias in dynamic panels, and the grouped fixed-effects (GFE) estimator to flexibly accommodate latent cross-country heterogeneity in the estimated effects of alternative credit. Doing so requires the augmentation of a lagged dependent variable into both Equations 1.2 and 1.4.

However, these dynamic extensions introduce Nickell bias in short panels where the cross-section dimension is large relative to the time series dimension. Standard fixed-effects estimators and 2SLS frameworks do not eliminate this bias. To address this issue, I implement the HPJ-FE estimator—introduced initially as a split-panel jackknife correction by Dhaene and Jochmans (2015) to mitigate Nickell bias in fixed-effects models—and subsequently extended by Chudik et al. (2018) to accommodate linear and dynamic panels with weakly exogenous regressors, making it particularly well-suited for macro-panel contexts. This estimator also addresses problems of weakly exogenous regressors, as it requires only weak exogeneity of the regressors. This estimator splits the panel along the time dimension, estimates separate fixed-effects models on each half, and averages the results to remove the bias introduced by lagged dependent variables. This estimator provides a consistent correction for dynamic bias and is well-suited to macro-panel settings. It also avoids the complications of instrument proliferation inherent in GMM methods.

In addition, this study applies the grouped fixed-effects (GFE) estimator, developed by Bonhomme and Manresa (2015), to capture latent heterogeneity in cross-country responses to alternative credit. Unlike the standard fixed-effects approaches that are arguably restrictive, which assume that unobserved heterogeneity is constant over time, GFE assigns units to latent groups based on shared dynamic patterns and allows for group-specific unobserved heterogeneity (Bonhomme & Manresa, 2015). Applying this method to both the bank credit and financial stability models enables an examination of whether countries cluster into unobserved groups that respond differently to alternative credit, reflecting variation in financial infrastructure and regulatory frameworks. This approach offers a structured alternative to conventional fixed effects by pooling countries with similar unobserved characteristics and allowing group-specific intercepts. I re-estimate Equations 1.2 and 1.4, each including its respective lagged dependent variable, using the grouped fixed-effects estimator. The results are then compared to the baseline specification to assess the robustness of the estimated effect of alternative credit on traditional bank credit.

3.5 Hypotheses of the Study

This study formulates the following hypotheses—grounded in both theoretical frameworks and empirical evidence—to investigate the relationship between alternative credit and traditional banking, its implications for financial stability, and the moderating role of systemic shocks.

Hypothesis 1: Complementarity or Substitution Between Alternatives and Bank Credit

The empirical literature remains divided on whether alternative credit acts as a complement to or a substitute for traditional bank lending. Some studies argue that alternative lenders compete directly with banks, particularly in concentrated credit markets, thereby displacing bank loans and eroding interest income (Bofondi & Infante, 2017; Doerr, Frost, et al., 2023; Hodula, 2022; Tang, 2019). Others emphasize complementarity: by extending credit to underserved segments such as SMEs and subprime borrowers, alternative lenders may relieve informational and collateral constraints, allowing banks to reallocate capital more efficiently and expand overall credit supply (Buchak et al., 2018; Thakor, 2020). In addition, incumbent banks may strategically adjust their lending models in response to competition from digital platforms (Cornelli et al., 2020; Financial Stability Board, 2022).

Given these divergent theoretical predictions and empirical findings, the analysis does not impose ex-ante assumptions on the nature of the relationship. Instead, it tests whether alternative credit complements or substitutes for conventional bank credit.

- **H1a:** $\psi > 0 \implies$ Alternative credit complements traditional bank credit.
- **H1b:** $\psi < 0 \implies$ Alternative credit substitutes for traditional bank credit.

A negative estimated coefficient (ψ) on alternative credit implies partial displacement of bank lending, consistent with a substitution effect. Conversely, a positive coefficient indicates that alternative credit complements bank credit, enhancing financial inclusion.

Hypothesis 2: Alternative Credit and Financial Stability

The impact of alternative credit on financial stability is theoretically ambiguous. On the one hand, alternative lenders may strengthen stability by fostering credit diversification, enhancing market efficiency through technological innovation, lowering transaction costs, and improving borrower screening through advanced data analytics (Gambacorta et al., 2024). These mechanisms may reduce the likelihood of systemic banking failures and improve overall credit resilience. On the other hand, alternative credit channels may undermine stability if they erode underwriting standards, encourage procyclical lending, or rely excessively on transactional and non-traditional data. These risks are particularly salient in downturns and under weak regulatory oversight. Vuković et al. (2024) finds that FinTech credit increases bank risk during periods of stress by weakening credit quality. Similarly, Financial Stability Board (2022) warns that rapid, opaque growth in alternative credit can amplify systemic vulnerabilities through excessive risk-taking and insufficient supervision.

- **H2a:** $\psi > 0 \implies$ Alternative credit enhances financial stability.

- **H2b:** $\psi < 0 \implies$ Alternative credit reduces financial stability.

The empirical model does not impose an a priori expectation on the direction of the effect; instead, it evaluates the net outcome across countries with varying regulatory quality, market maturity, and FinTech penetration.

Hypothesis 3: The Moderating Effect of External Shocks (Shock Transmission)

External shocks—such as the COVID-19 pandemic—may alter the relationship between alternative credit and conventional bank credit. The interaction coefficient δ_2 between alternative credit and COVID-19 captures this moderation effect in the extended specification. A negative value of δ_2 implies that a shock dampens alternative credit's influence on traditional bank credit, weakening the complementarity or substitution mechanism.

- **H3a:** $\delta_2 < 0$ in equation (1.2) $\implies$ External shocks weaken the effect of alternative credit on traditional bank credit.

Similarly, systemic shocks provide an opportunity to assess the resilience of alternative credit in supporting financial stability. Although digital lending platforms may absorb some frictions during periods of market stress, they may also amplify volatility through procyclical lending, limited oversight, or weaker borrower screening (Doerr, Frost, et al., 2023; Frost, 2020; Vuković et al., 2024). It is therefore hypothesized that the stabilizing effect of alternative credit declines during crises such as the COVID-19 pandemic.

- **H3b:** $\delta_2 < 0$ in equations (1.3 and 1.4) $\implies$ External shocks attenuate alternative credit's stabilizing effect.

Hypothesis 4: BigTech Amplification during Crises

BigTech lenders operate at scale, leveraging vast datasets, ecosystem integration, and network effects that may amplify their systemic footprint (Chen et al., 2021; Frost et al., 2019; FSB, 2019). Unlike FinTech platforms, which typically focus on narrower segments or single-function services, BigTech firms possess broad consumer platforms that integrate payments, lending, e-commerce, and digital identity. These features can exacerbate procyclical dynamics during crises, particularly through behavioral data feedback loops—such as declining consumption or search behavior reducing credit access through algorithmic scoring.

During systemic shocks, BigTech credit may thus exert a more destabilizing influence than FinTech credit. Vuković et al. (2024) highlights how BigTech credit, due to its dominance and reliance on real-time behavioral data, can accelerate financial contagion and amplify external shocks. In such contexts, BigTech lenders may crowd out traditional credit more aggressively and propagate stress through multiple market channels.

To test this hypothesis, I estimate Equation (1.2) separately for BigTech and FinTech credit, each interacted with a crisis indicator (e.g., COVID-19), and compare their effects on financial stability using a Wald test:

$$\text{Wald test: } H_0 : \psi_{\text{BigTech}} = \psi_{\text{FinTech}} \quad \Rightarrow \quad \text{Rejecting } H_0 \text{ implies differential effects.}$$

A significantly more negative coefficient for BigTech credit under crisis conditions would support the hypothesis that its systemic footprint and data-driven operational model render it more destabilizing during periods of economic stress.

4 Results and Discussion

This section presents and discusses the empirical findings. It first examines the relationship between alternative credit and conventional bank credit, followed by an analysis of the impact of alternative credit on financial stability, and how this relationship is influenced by the COVID-19 pandemic as an exogenous shock.

The first part investigates the link between alternative credit and traditional bank lending. A two-stage least squares (2SLS) instrumental variable approach is employed, using mobile phone penetration and fixed broadband subscriptions as instruments for FinTech and BigTech credit, following the methodology of Hodula (2022) and Cornelli et al. (2020). Instrument validity is confirmed by the Hansen J test, which supports the exclusion restriction, and the Cragg–Donald F-statistic, which indicates strong instrument relevance. Table A3 confirms that the instruments satisfy both conditions.

Table 1.1 reports the first-stage estimation results from Equation 1.1. The specification includes controls for income group, geographic region, year fixed effects, and additional exogenous covariates. Column (1) presents results for FinTech credit, while columns (2) and (3) correspond to BigTech credit and the aggregated alternative credit variable, respectively. In all cases, the coefficients on mobile subscriptions and broadband access are positive and statistically significant, confirming the relevance of digital infrastructure in explaining the expansion of digital lending. These findings align with prior evidence from Emara and Mohieldin (2023), Selim Elekdag (2024), and Cuadros-Solas et al. (2024), which underline the critical role of technological foundations in enabling FinTech and BigTech credit markets.

The COVID-19 pandemic appears to have facilitated the expansion of all forms of alternative credit. Restrictions on mobility and the decline of in-person transactions prompted both individuals and firms to increasingly rely on digital platforms for credit access. This shift likely reflected the relative safety and convenience of remote financial services compared to the in-person procedures typical of conventional banking. Consistent with these dynamics, Fu and Mishra (2022) and Khakan Najaf and Atayah (2022) document a surge in digital credit usage during the pandemic, driven by reduced physical access to traditional institutions and evolving borrower preferences.

Table 1.1: First Stage IV Regression

	(1) FinTech Credit	(2) BigTech Credit	(3) Alt. Credit
Mobile subscriptions	0.851***	0.236***	0.907***
	(0.257)	(0.069)	(0.301)
Broadband subscriptions	0.446**	0.164*	0.528**
	(0.226)	(0.085)	(0.268)
GDP per capita	0.057	-0.340	-0.662
	(0.717)	(0.216)	(0.876)
Bank branches	0.130	0.032	0.114
	(0.266)	(0.126)	(0.293)
Governance indicator	1.819***	-0.105	1.309**
	(0.534)	(0.221)	(0.597)
Interest rate	0.011	0.008***	0.014
	(0.014)	(0.003)	(0.014)
COVID-19	0.580**	0.810**	0.485*
	(0.271)	(0.380)	(0.289)
Data regulation	0.298	0.125	0.404
	(0.396)	(0.213)	(0.427)
Bank Regulatory index	0.315	0.411	0.741
	(1.250)	(0.510)	(1.476)
ROA	0.142***	-0.005	0.153***
	(0.020)	(0.052)	(0.020)
Population growth	-0.065	0.040*	0.064
	(0.212)	(0.023)	(0.246)
Constant	-21.408***	-0.694	-25.546***
	(7.275)	(2.385)	(8.921)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Income Group FE	Yes	Yes	Yes
Adj. R^2	0.208	0.386	0.143
N	286	112	286

BigTech, FinTech, and alternative credit have been winsorized at the 1% and 99% levels. All regressors are lagged except for the instrument's mobile and broadband subscriptions and the dummies. This table presents results for Equation 1.1, where the dependent variables are the log of FinTech credit (column 1), BigTech credit (column 2), and alternative credit (column 3). The sample covers six geographic regions—Africa, Asia Pacific, Europe, Latin America, the Middle East, and North America—and is divided into four income groups based on World Bank classifications: high income, upper middle income, lower middle income, and low income.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results in Table 1.2 reveal a statistically significant and positive association between alternative credit and conventional bank credit, indicating a relationship of complementarity rather than substitution. Specifically, a 1% increase in alternative credit, holding all else constant, is associated with a 0.037% increase in conventional bank credit while

Table 1.2: Second Stage IV Regression

	(1) Bank Credit	(2) Bank Credit	(3) Bank Credit
Alt. credit	0.037***		
	(0.011)		
FinTech credit		0.054***	
		(0.017)	
BigTech credit			0.117***
			(0.022)
GDP per capita	-0.261**	-0.300**	5.512
	(0.113)	(0.131)	(6.368)
Bank Branches	0.200***	0.208***	4.039
	(0.048)	(0.054)	(4.884)
Governance indicator	0.271***	0.305***	15.357***
	(0.072)	(0.080)	(5.340)
Interest rate	-0.001	-0.001	-0.123
	(0.001)	(0.001)	(0.098)
Covid-19	-0.094***	-0.102***	-3.361***
	(0.015)	(0.017)	(1.268)
Data regulation	-0.074**	-0.048	2.634*
	(0.033)	(0.033)	(1.547)
Population growth	-0.003	-0.003	6.080***
	(0.011)	(0.012)	(1.300)
Bank regulatory index	-0.029	-0.033	-1.056
	(0.025)	(0.028)	(1.316)
ROA	-0.015***	-0.017***	1.723*
	(0.004)	(0.004)	(1.042)
Liquidity	-0.004***	-0.003***	0.008
	(0.001)	(0.001)	(0.055)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
IncomeGroup FE	Yes	Yes	Yes
Adj. R^2	0.154	0.233	0.625
N	430	429	129

BigTech, FinTech, alternative credit, and conventional bank credit have been winsorized at the 1% and 99% levels. All regressors are lagged and expressed in natural logarithmic form, except for BigTech credit and the dummy variables. Given the prevalence of zero observations in BigTech credit, the variable is included in levels and expressed in millions of USD. The table reports estimates from Equation 1.2, with conventional bank credit as the dependent variable. Column (1) examines the effect of alternative credit, Column (2) focuses on FinTech credit, and Column (3) analyzes the role of BigTech credit. The sample is stratified by four World Bank income groups: high income, upper middle income, lower middle income, and low income.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

a similar increase in FinTech credit is associated with a 0.054% increase. For BigTech credit—measured in levels—a one million USD increase corresponds to a 0.12 unit rise in bank credit. These findings suggest that the expansion of digital lending channels complements conventional banking by broadening credit access and reinforcing overall credit market activity.

The findings reinforce the view that credit provided by technology firms complements, rather than substitutes, conventional bank credit. This complementarity likely operates through multiple channels. First, FinTech platforms often reach segments underserved or excluded by traditional banks. By offering initial credit access, they enable individuals to build financial histories, which can later facilitate entry into formal banking. Frost et al. (2020) and Berg et al. (2020) provide empirical support for this pathway, showing that FinTech expands credit access and ultimately enhances banks' capacity to evaluate and onboard new clients.

Second, the presence of FinTech may introduce competitive pressures that encourage banks to improve operational efficiency through digital transformation (Sheng, 2021; Thakor, 2020). This technological adaptation can streamline screening procedures, lower costs, and increase service accessibility. Third, rather than operating in direct competition, banks increasingly engage in strategic partnerships with FinTech firms, integrating their advanced scoring models and digital infrastructures. In return, FinTech firms gain access to banks' capital bases and regulatory know-how. Doerr, Frost, et al. (2023) argues that such alliances can enhance bank efficiency and foster broader financial inclusion. These dynamics are consistent with the evidence reported by Hodula (2022) and Murinde et al. (2022), suggesting that alternative credit is not displacing traditional lending but instead contributing to a rather harmonious co-existence.

The governance indicator, measured as the average of the World Governance Indicators, is positively associated with all forms of credit. This relationship suggests that stronger institutional quality supports credit expansion across both conventional and alternative channels. Effective governance likely improves contract enforcement, mitigates information asymmetries, and fosters trust in both digital and formal financial systems, thereby enhancing credit market functioning. Similarly, the coefficients on bank branches are consistently positive and statistically significant in the models for alternative and FinTech credit. This indicates that a more extensive physical banking network remains correlated with higher levels of conventional credit, underscoring the continuing relevance of brick-and-mortar infrastructure in facilitating credit provision, even in an environment increasingly shaped by digital lending platforms.

To assess the validity of the instrumental variable estimates, Table A3 reports the Hansen J statistic, the first-stage F-statistics, the Cragg-Donald Wald F statistic for weak identification, and the Anderson-Rubin Wald (ARW) test. The results indicate that the estimates are robust to weak instrument concerns. Details are provided in Table A3.

To extend the baseline analysis, the model incorporates interaction terms between alternative credit and two key external shocks: data privacy regulation and the COVID-19 pandemic. Table 1.3 presents the results. Column (1) includes data privacy regulation and its interaction with alternative credit. Column (2) introduces the COVID-19 shock and its corresponding interaction term. Column (3) combines both interactions, allowing for a joint assessment of how alternative credit responds to concurrent regulatory and pandemic-induced disruptions.

Across all specifications, both privacy regulation and the pandemic are associated with a contraction in bank credit supply. Regulations such as the General Data Protection Regulation (GDPR) limit banks' ability to utilize customer data effectively, raise compliance costs, and prolong credit evaluation processes. Buchak et al. (2018) highlights that such frictions can reduce credit supply by increasing operational burdens and weakening data-driven lending efficiency. These effects likely compound the already stringent regulatory environment faced by banks, particularly in markets reliant on granular data for credit assessment. The COVID-19 pandemic similarly introduced substantial uncertainty, prompting more conservative lending behavior. As documented by Demirgüç-Kunt et al. (2020), the crisis period was marked by tighter credit conditions, driven by rising borrower risk and heightened macro-financial volatility.

The interaction terms reveal how these shocks attenuate the positive association between alternative credit and traditional bank lending. The negative and statistically significant coefficient on the interaction between alternative credit and privacy regulation suggests that the complementarity between digital and conventional credit channels weakens under stricter data governance. This may reflect constraints in data sharing and reduced precision in credit analytics, which impair the ability of alternative lenders to contribute to broader intermediation. Likewise, the negative interaction with the COVID-19 shock indicates that pandemic-related risks disrupted the reinforcing effect of alternative credit. Although digital platforms scaled rapidly during the crisis, rising defaults and liquidity concerns may have diminished banks' willingness to extend credit, thereby reducing the system-wide stabilizing role of alternative credit.

Table 1.3: Bank and Alternative Credits Relationship (Accounting for Shocks)

	Bank Credit	Bank Credit	Bank Credit
Alternative credits	0.074***	0.046***	0.052**
	(0.026)	(0.017)	(0.021)
GDP per capita	-0.337**	0.167***	0.173***
	(0.162)	(0.060)	(0.060)
Bank Branches	0.199***	0.154***	0.162***
	(0.061)	(0.035)	(0.034)
Governance indicators	0.335***	0.321***	0.321***
	(0.094)	(0.052)	(0.053)
Bank regulatory index	-0.031	0.065	0.078
	(0.031)	(0.139)	(0.143)
ROA	-0.020***	-0.052***	-0.053***
	(0.005)	(0.015)	(0.014)
Liquidity	-0.003***	-0.003*	-0.003*
	(0.001)	(0.002)	(0.002)
Data Regulation	-0.230**	0.003	-0.209*
	(0.077)	(0.053)	(0.171)
Covid-19	-0.105***	-0.274*	-0.251***
	(0.019)	(0.216)	(0.217)
PrivacyShock*AC	-0.038***		-0.035*
	(0.013)		(0.024)
CovidShock*AC		-0.040*	-0.039*
		(0.023)	(0.023)
Constant	4.721***	2.566***	2.506***
	(0.783)	(0.634)	(0.629)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
IncomeGroup FE	Yes	Yes	Yes
Adj.R-squared	0.607	0.726	0.723
N	430	442	442

Alternative credit and conventional bank credit have been winsorized at the 1% and 99% levels. All regressors are lagged and in natural logarithmic form, except for the dummy variables. This table presents results for Equation 1.2, where the dependent variable is the conventional bank credit. It examines the relationships between conventional bank credit and alternative credit, incorporating interactions with privacy regulation (column 1), COVID-19 shocks (column 2), and both interactions (column 3). The sample includes six geographic regions—Africa, Asia Pacific, Europe, Latin America, the Middle East, and North America—and is categorized into four income levels: high income, upper middle income, lower middle income, and low income. Population growth rate and real interest rate are estimated but not reported for brevity.

Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The analysis that follows examines whether alternative credit contributes to financial stability. Table 1.4 presents the results from estimating Equation 1.3 using a two-way fixed effects model, consistent with the view that alternative credit can enhance financial stability, as suggested by FSB and CGFS (2017), Philippon (2016), and Hornuf et al. (2021). The dependent variable is the banking system's Z-score. Column (1) includes the aggregate measure of alternative credit alongside standard control variables. Columns (2) and (3) separately examine the effects of FinTech credit and BigTech credit. Across all specifications, the coefficients on alternative, FinTech, and BigTech credit are positive and statistically significant, indicating that greater access to these non-traditional credit sources is associated with enhanced banking sector stability.

Technology firms contribute to financial stability by promoting diversification and decentralization in the provision of financial products and services. This diversity reduces systemic vulnerability by limiting the consequences of distress at any single institution (FSB & CGFS, 2017). It also enhances the efficiency of financial intermediation by offering innovative and cost-effective products that benefit both consumers and traditional banks. The expansion of mobile technology has played a key role in broadening access to financial services and supporting the development of open banking frameworks (Lenka & Barik, 2018). Furthermore, technology firms facilitate the rapid dissemination of information across platforms, contributing to more responsive capital markets that better reflect real-time conditions. By lowering transaction costs, improving risk assessment, and strengthening data processing capabilities, they help mitigate information asymmetries that often lead to credit market failures (Koranteng & You, 2024; Philippon, 2016).

It is also important to note that technology firms generally exhibit lower financial interconnectedness levels than banks. This structural feature suggests that the alternative credit market may be more resilient to systemic shocks, particularly those originating in the traditional banking sector. Unlike banks, which are often highly interlinked through interbank exposures, technology-based lenders operate with greater autonomy. This independence may offer an additional stabilizing mechanism during periods of financial distress (FSB & CGFS, 2017).

As indicated in Table 1.4, a 1% increase in FinTech, BigTech, and alternative credit leads to a 0.006%, 0.001%, and 0.007% rise in the banking Z-score, respectively. While these results are statistically significant, their economic impact is relatively modest. The

Table 1.4: Impact of Alternative Credit on the Financial Stability

	(1)	(2)	(3)
Alternative Credit	0.007*		
	(0.004)		
FinTech credit		0.006*	
		(0.004)	
BigTech credit			0.001***
			(0.000)
Covid19	-0.124***	-0.096**	-0.132**
	(0.045)	(0.040)	(0.060)
Bank Branches	0.065***	0.039	0.067**
	(0.024)	(0.035)	(0.034)
Domestic Credit	0.003	-0.163	-0.029
	(0.119)	(0.129)	(0.149)
margin	0.151***	0.157***	0.151**
	(0.058)	(0.060)	(0.060)
GDP per capita growth	0.019*	0.012	0.012
	(0.011)	(0.016)	(0.010)
Inflation	-0.000	-0.001	-0.000
	(0.004)	(0.003)	(0.005)
Openness	-0.255**	-0.175	-0.182
	(0.129)	(0.125)	(0.128)
Governance indicator	0.044	0.093	0.098
	(0.121)	(0.117)	(0.127)
Constant	5.618***	3.886***	4.472***
	(1.388)	(1.417)	(1.499)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Adj.R-squared	0.406	0.485	0.438
N	146	152	109

Notes: The table shows the results of the two-way fixed effects regression for Equation 1.3, with the dependent variable being the Z-score. It provides the outcomes when financial stability is regressed on alternative credit (column 1), FinTech credit (column 2), and BigTech credit (column 3), along with other external control variables. GDP per capita growth, NPL, and concentration are estimated but not reported. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

findings suggest that improved credit access through technology firms enhances banking stability and underscores the growing role of these firms in financial stability. The positive effect indicates that technology firms' credit helps meet unmet credit demand, boosting economic activity. Moreover, their presence increases competition for traditional banks, potentially driving innovation and improvements in banking services. These findings align with the works of Daud et al. (2022), Koranteng and You (2024), and Murinde et al. (2022), who also find that alternative financing positively contributes to financial stability.

The COVID-19 shock has been found to have a negative and significant effect on financial stability. However, the magnitude of this effect may be understated since the analysis only captures its immediate impact during the year 2020. Net interest margin plays a positive role in shaping financial risk behavior. This study aligns with Saksonova (2014), who argues that a larger net interest margin implicates banks' successful management of interest-bearing assets, which in turn reduces banks' risk of default. The Bank branch network, which proxies the outreach of financial services, is also a statistically significant factor in improving the banking system's financial stability.

Table A14 presents the effect of FinTech, BigTech, and alternative credit interacting with the COVID-19 shock on financial stability. COVID-19 has a negative and significant impact on banking stability, and when combined with BigTech credit, it further increases banking fragility. The negative interaction between COVID-19 and BigTech credit indicates that COVID-19 shock offsets the positive effect of BigTechs on financial stability and increases the fragility of the banking system by 0.025 percentage points. This implies that the financial disruptions caused by COVID-19, such as increased uncertainty and loan defaults, reduce the ability of alternative credit to support stability during times of crisis.

Moreover, the interaction effect is more pronounced for BigTech than for FinTech credit, in line with the hypothesis that BigTech firms amplify systemic stress due to their scale, ecosystem integration, and behavioral-data-driven lending models. These features increase their systemic footprint and can exacerbate procyclical dynamics during crises through algorithmic responses to real-time consumption and platform activity (Chen et al., 2021; Frost et al., 2019; FSB, 2019). As noted by Vuković et al. (2024), such feedback loops may accelerate contagion and amplify external shocks, making BigTech credit a more potent transmission channel during systemic crises than FinTech credit.

Additional control variables also have a significant impact on the stability of the conventional banking system. Bank branch networks and net interest margins enhance financial stability. In contrast, economic openness, measured as the sum of imports and exports relative to GDP, negatively affects banks' resilience to default risk, likely due to increased exposure to external shocks, exchange rate volatility, and fluctuations in capital flows.

All the results of the Table A14 account for geographic region and year fixed effects.

Table A15 further shows the transmission channel through which COVID-19 impacts financial stability. The interaction effects of COVID-19 with various economic indicators reveal that wealthier countries may face more significant negative impacts on financial stability, as indicated by the negative coefficient for GDP per capita. In contrast, increased domestic credit can mitigate these adverse effects, enhancing resilience. Inflation further exacerbates instability, while more bank branches provide a buffering effect. However, higher margins during the pandemic contribute negatively to financial health, emphasizing the complex interplay between COVID-19 and economic factors that influence financial stability.

5 Robustness Tests and Alternative Approaches

This section presents a series of robustness checks and alternative estimation strategies to assess the stability of the results. The analysis proceeds in two parts. First, I test the robustness of the relationship between alternative credit and traditional bank credit. Second, I examine the association between alternative credit and financial stability using additional specifications and estimators.

Relationship Between Traditional Bank Credit and Alternative Credit

Several alternative specifications are estimated to test the robustness of the baseline results. First, the model includes fixed effects by geographical region. The results, reported in Table A4, remain consistent with the baseline estimates. Second, the level values (in USD) of bank credit, FinTech credit, and BigTech credit are used instead of logarithmic transformations. Table A5 reports the second-stage results. Across all variants of Equations 1.1 and 1.2 for alternative, FinTech, and BigTech credits, the estimates align with those presented in Tables 1.1 and 1.2. Mobile and broadband subscriptions continue to exhibit a positive and statistically significant effect on access to BigTech, FinTech, and total alternative credit. All forms of alternative credit consistently complement traditional bank credit.

Third, to examine heterogeneity across development levels, the sample is split by income group. This approach is motivated by the literature suggesting that higher-income countries more rapidly adopt financial innovations (Claessens et al., 2018; Cornelli et al., 2020; Frost et al., 2019) and that income levels condition the effect of alternative credit on financial inclusion (Demir et al., 2022). For this analysis, the low-income group comprises all countries classified by the World Bank as upper-middle-income, lower-middle-income, or low-income. Tables A6 and A7 present the results for high- and low-income countries, respectively. In both groups, access to BigTech, FinTech, and alternative credit remains positively associated with traditional bank credit. These findings are consistent with those reported by Demir et al. (2022) and Hodula (2022).

Fourth, to rule out the influence of outlier economies with disproportionately large volumes of alternative credit, the United States and China are excluded from the sample. Table A8 presents the results based on Equation 1.2. The estimated coefficients remain stable and consistent with the baseline findings, confirming that the results are not driven by these two dominant markets.

To mitigate potential biases in fixed effects and standard 2SLS estimators, I employ a Half-Panel Jackknife Fixed Effects (HPJ-FE) approach, which averages estimates from split panel samples. The results show that alternative credit has a positive effect on traditional bank credit (0.0027). FinTech credit exhibits a positive and statistically significant effect (0.0117), supporting the interpretation that it complements bank lending—likely through shared customer bases or technological spillovers. BigTech credit also displays a positive association (0.0069), though the effect is comparatively weaker. Across all specifications, the lag of bank credit remains strongly persistent, and the COVID-19 shock consistently reduces credit supply. These findings underscore the differentiated roles of FinTech and BigTech, with FinTech showing a more consistent integration into the traditional credit system.

Results indicate that all forms of alternative credit positively affect traditional bank credit, albeit with varying magnitudes. The overall effect of alternative credit is modest (HPJ-FE: 0.0027), while FinTech credit shows a stronger and economically meaningful association with bank credit (HPJ-FE: 0.012). BigTech credit also exerts a positive effect (HPJ-FE: 0.0069), though its magnitude is smaller than that of FinTech. Across all specifications, the lag of bank credit remains highly persistent, and the COVID-19 shock is consistently associated with a contraction in credit supply. These findings support the view that alternative forms of digital lending complement conventional bank credit. Moreover, they highlight the heterogeneous influence of FinTech and BigTech credit on banking sector dynamics, with FinTech exhibiting more consistent integration, potentially via customer acquisition, credit scoring spillovers, or shared digital infrastructure.

Lastly, the Grouped Fixed Effects (GFE) model is implemented as a robustness check to address unobserved heterogeneity across countries, with coefficient estimates presented in Table A19. Following the methodology of Bonhomme and Manresa (2015), the GFE framework endogenously classifies the sample into three latent groups based on shared structural patterns and time-varying heterogeneity. This approach permits slope heterogeneity across groups, offering greater flexibility than conventional fixed effects models that impose coefficient homogeneity. The results indicate that alternative credit complements conventional bank credit. However, the strength and statistical significance of these effects vary by group. FinTech credit consistently exhibits a positive relationship with bank credit, though the effect is weaker in lower-tier segments. Alternative credit also shows a broadly positive association, reinforcing the complementarity hypothesis. By contrast, BigTech credit reveals notable heterogeneity

On the Relationship Between Alternative Credit and Financial Stability

Several robustness checks are conducted to examine the relationship between alternative credit and financial stability. First, the log-transformed credit variables are replaced with level values (in USD) for bank credit, FinTech credit, and BigTech credit. Table A9 presents results from Equation 1.3, where financial stability is regressed on alternative credit (column 1), FinTech credit (column 2), and BigTech credit (column 3), along with standard control variables. The estimates remain consistent with the baseline findings, reinforcing the robustness of the main results.

Second, a two-stage least squares (2SLS) framework is applied, as specified in Equation 1.4, to address potential endogeneity in the alternative credit market. In the first stage, mobile and broadband subscriptions strongly predict access to BigTech, FinTech, and overall alternative credit, confirming instrument relevance. The second-stage estimates are reported in Tables A11 and A13, with the former showing reduced-form results and the latter including the usual exogenous controls. These 2SLS findings align with the two-way fixed effects model, suggesting that greater access to FinTech and BigTech credit enhances financial stability and mitigates banking sector fragility. Third, the Half-Panel Jackknife Fixed Effects (HPJ-FE) estimator is employed to account for the dynamic nature of financial stability, which exhibits strong inertia over time. While the inclusion of lagged dependent variables in standard fixed effects models introduces Nickell bias, HPJ-FE corrects for this distortion and provides more reliable estimates. As expected, the lagged values of alternative, FinTech, and BigTech credit are positively associated with financial stability, supporting the view that stability evolves gradually due to persistent structural and behavioral dynamics within the banking sector. This finding is consistent with the arguments of Granger (1969), Hornuf et al. (2021), and Stock and Watson (2020), who underscore the importance of lag structures in capturing unobserved, time-varying heterogeneity.

The HPJ-FE coefficients are derived from two specifications. The first is based on the fixed effects model in Equation 1.3, which includes the lag of the Z-score to capture persistence. The second builds on the 2SLS approach in Equation 1.4, incorporating fitted values of alternative credit derived from instrumental variable estimation to address endogeneity. In both cases, the panel is split into early and late subsamples to implement the jackknife bias correction. The corresponding results are presented in Tables A17 and A18, with the former based on the fixed effects specification.

The HPJ-FE estimates show that all forms of alternative credit are positively associated with financial stability, though the effects vary in magnitude. Aggregate alternative credit yields a modest stabilizing effect (0.0085), while FinTech credit exhibits a stronger influence (0.0100), likely due to its focus on small-scale, data-driven lending that broadens access to credit. BigTech credit, while statistically significant, has a relatively minor effect (0.0004), suggesting a weaker link to systemic resilience. The positive and significant coefficients on the lagged Z-score across all models confirm the persistence of financial stability. The COVID-19 shock is consistently associated with a pronounced decline in stability. Among the control variables, higher net interest margins are linked to increased fragility, whereas branch density enhances stability in the BigTech specification. Overall, the results reinforce the conclusion that both FinTech and BigTech credit contribute—albeit modestly—to banking sector stability.

The Grouped Fixed Effects results on Table A20 reveal that all forms of alternative credit—AltCredit, FinTech, and BigTech—exhibit a positive and statistically significant association with financial stability, measured by the Z-score, though the magnitude and consistency of effects vary across latent country groups. AltCredit demonstrates a modest but stable contribution to financial stability across all groups, supporting the complementarity hypothesis. FinTech credit yields the strongest and most consistent positive effects in Groups 0 and 2, indicating that its stabilizing role may be more pronounced in economies with advanced digital infrastructure or adaptive regulatory frameworks. By contrast, its impact is negligible and statistically insignificant in Group 1, suggesting heterogeneity in institutional or market readiness. BigTech credit also shows a significant positive relationship with stability in all groups, albeit with smaller effect sizes. The relatively changed impact of BigTech lending may reflect greater regulatory scrutiny or higher systemic risk buffers embedded in such platforms. Overall, the results emphasize that while alternative credit enhances banking sector resilience, the channels and intensity of impact differ by credit type and country context.

6 Conclusions and Policy Implications

This paper examines two central questions in the evolving credit landscape: whether alternative credit, including FinTech and BigTech credits, complements or substitutes traditional bank credit, and whether it contributes to financial stability. Using a panel of 145 countries from 2013 to 2020, the analysis applies instrumental variable estimation, fixed effects models, and bias-corrected dynamic panel methods of HPJ-FE and group fixed effects to evaluate the role of alternative credit under normal conditions and in the presence of external shocks.

The results indicate that alternative credit complements conventional bank credit, with FinTech credit showing a particularly strong positive association. This complementarity likely arises from the ability of FinTech firms to reach underserved segments excluded from formal banking, thereby expanding the pool of bankable clients. Banks may also benefit from adopting FinTech tools, such as improved credit scoring models. Furthermore, partnerships between banks and technology firms create mutually reinforcing dynamics: while banks leverage digital innovations, FinTech firms access capital and regulatory expertise. However, this complementarity is context-dependent. The analysis shows that external shocks weaken the relationship between alternative and traditional credit, likely by increasing credit risk, disrupting data usage, and tightening lending conditions.

The study also finds that alternative credit contributes modestly to financial stability. FinTech credit, in particular, is associated with stronger stability gains than BigTech credit, possibly due to its smaller scale and more targeted, short-term lending. The decentralization of credit sources and lower systemic interconnectedness of FinTech lenders appear to limit risk concentration. While the COVID-19 shock reduced the stabilizing effects of BigTech credit, FinTech credit maintained a more consistent contribution to financial stability, even under stress. This suggests that although alternative credit channels are not immune to macro-financial volatility, their role in supporting systemic resilience remains relevant when supported by appropriate regulatory frameworks.

This study yields several policy-relevant insights regarding the role of alternative credit in financial systems. However, given the modest and context-specific nature of the findings, they should be interpreted cautiously. First, the evidence suggests that alternative credit can play a complementary role to traditional bank credit rather than acting as a substitute. This implies that regulatory approaches that foster collaboration between banks and digital lenders, rather than treating them as competing entities, may yield efficiency gains and broaden credit access. Policies that encourage interoperability and facilitate responsible partnerships between banks and FinTech firms could amplify these complementarities. In particular, promoting channels through which banks can adopt or integrate FinTech innovations, such as alternative credit scoring tools, may improve credit allocation without undermining financial stability.

Second, the results show that the positive association between alternative credit and bank lending is sensitive to exogenous shocks like the COVID-19 pandemic. These shocks attenuate the complementarity between digital and conventional credit, likely by increasing uncertainty, limiting data availability, and raising compliance costs. This suggests that during periods of systemic stress or major regulatory transitions, complementary channels between traditional and digital finance may weaken. Accordingly, regulatory frameworks should be designed to remain adaptive under such conditions.

Third, while the analysis confirms a positive association between alternative credit and financial stability, the effect is economically modest. FinTech credit, in particular, appears to contribute more consistently to stability than BigTech credit. These findings suggest that FinTech lenders can modestly enhance resilience in credit markets, especially when they expand access in underbanked segments or diversify credit sources.

Finally, institutional factors such as the strength of governance and the density of the banking network also shape the effectiveness of alternative credit. Countries with stronger governance indicators and broader branch networks are associated with higher bank credit supply and more stable banking systems. These findings imply that the benefits of alternative credit depend on a supportive institutional environment. Therefore, in countries with weak regulatory capacity or fragmented digital infrastructure, the expansion of alternative credit should be accompanied by parallel investments in institutional development, digital access, and supervisory oversight.

Future research could examine the longer-term effects of alternative credit under different regulatory regimes and across economic cycles, particularly to assess whether its stability-enhancing properties persist during extended periods of financial stress. As this study focuses on the initial phase of the COVID-19 pandemic, further analysis could help clarify the durability of alternative credit's stabilizing role under prolonged or repeated shocks.

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Appendices

Appendices

Table A1: Description and Source of Variables

Variable	Definition & Source of variable
FinTech credit	FinTech credit per capita (in USD). FinTech credit encompasses digital lending models such as peer-to-peer (P2P) lending, invoice trading, and other debt-based alternative finance mechanisms facilitated through online platforms. Data obtained from CCAF.
BigTech credit	BigTech credit per capita (in USD). It refers to loans issued by large technology companies whose core operations lie outside the financial sector but increasingly engage in financial intermediation directly or in partnership with financial institutions. Data obtained from Cornelli et al. (2020) and Frost et al. (2019)
Alternative Credit	is a lending activity by non-traditional financial intermediaries, and it is the sum of credit extended by FinTech and BigTech providers. These credit volumes are measured on a per capita basis in USD.
ggdppc	Annual percentage growth rate of Gross Domestic Product per capita based on constant local currency and divided by midyear population.
GDPpc	GDP per capita is gross domestic product divided by midyear population. Data are in constant 2015 U.S. dollars. Obtained from the World Bank WDI.
GDPpc_sqr	GDP per capita square is a quadratic form of GDP to capture the non-linear relationship between income level and credit development in the economy i at period t.
BankBranches	Bank branches per 100,000 adults and capture the reach of the banking sector through their subsidiary retail or main office that provides financial services to customers. Obtained from the World Bank WDI.
CrisisDummy	A dummy for whether a country had suffered a financial crisis since 2006, as defined by Laeven and Valencia (2018)
Governance indicators	The World Governance Indicators (WGI) provide composite measures of institutional quality across six dimensions, including government effectiveness, regulatory quality, rule of law, and control of corruption. Each indicator is expressed on a standardized scale ranging from –2.5 (weak governance) to +2.5 (strong governance). The data are compiled annually by the World Bank.
Lerner_Index	Lerner Index measures the bank's market power in the banking sector markups and is normalized between 0 (perfect competition) and 1 (pure monopoly). Obtained from Global Financial Development Database (GFDD) and Igan et al. (2021).

Table A1: Description of Variables (*continued*)

Variable	**Definition & Source of variable**
Inflation	Rate of inflation are calculated as the annual change of the Consumer Price Index. It reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services. Data source: WDI
openness	Trade openness is the sum of exports and imports of goods and services measured as a percentage of GDP, and the data is obtained from WDI.
TotPopn	Total population, which counts all residents regardless of legal status or citizenship. The values shown are midyear estimates. Data obtained from WDI.
Popln growth.rate	Annual population growth rate expressed as a percentage. Data obtained from WDI.
trust_index	Proxied by the following three proxies. A percentage of year 15 and above population (i) who made or received a digital payment, (ii) who made a digital online merchant payment for an online purchase, and (iii) who used a mobile phone or the internet to buy something online. These three proxies are weighted and normalized into a trust index that ranges between 0 (no trust) and 1 (maximum trust). Data was obtained from the World Bank gender data portal.
Mobsubscrper100ppl	Mobile cellular subscriptions (per 100 people). It applies to all mobile cellular subscriptions that offer voice communications. Data comes from the International Telecommunication Union (ITU).
broadbndper100ppl	Fixed broadband subscriptions (per 100 people). Data comes from the ITU.
GDPR shock	General Data Protection Regulation dummy that is 1 from the year of the policy implementation (2018) and 0 for the pre-2018.
Covid-19	I Several measures of the COVID-19 pandemic were employed, including new confirmed cases per capita, hospitalization rates, and COVID-related death rates, following Ng (2021). Data were obtained from Mathieu et al. (2020) and the Oxford COVID-19 Government Response Tracker (OxCGRT) developed by Hale et al. (2021). An additional approach involved a binary COVID-19 indicator, coded as 1 for countries reporting COVID-related deaths in 2020 and 0 for all other country-year observations.
dom_private_credit	Domestic credit to the private sector (% of GDP). Financial resources provided to the private sector by financial corporations, such as loans, purchases of nonequity securities, trade credits, and other accounts receivable, establish a claim for repayment.
dom_credit	Domestic credit provided by the financial sector (% of GDP). It includes all credit to various sectors on a gross basis, with the exception of credit to the central government, which is net.
margin	Bank's net interest margin; measured as the value of banks' net interest revenue as a share of its average interest-bearing (total earning) assets.
real_ir	Real interest rate is the lending interest rate adjusted for inflation (%).

Table A1: Description of Variables (*continued*)

Variable	**Definition & Source of variable**
capital adequacy	Capital adequacy of deposit takers. It is a ratio of total bank regulatory capital to its assets held, weighted according to the risk of those assets (%).
npl	Bank non-performing loans to gross loans (%). The ratio of defaulting loans (payments of interest and principal past due by 90 days or more) to total gross loans (total value of loan portfolio). Nonperforming loans include the gross value of the loan as recorded on the balance sheet, not just the overdue amount.
Provison_npl	Provisions to nonperforming loans (%).
roa	Return on average assets calculated as commercial bank's net income to yearly averaged total assets (%).
borr	Borrowers from commercial banks (per 1,000 adults). These are the reported numbers of resident customers that are nonfinancial corporations (public and private) and households who obtained loans from commercial banks and other banks functioning as commercial banks. Data from WDI.
liquidity	The ratio of liquid assets to deposits and short-term funding. Liquid assets include cash due from banks, trading securities at fair value, loans and advances to banks, reverse repos, and cash collaterals. Deposits include current, savings, and term, and short-term funding includes money market instruments and CDs (%).
zscore	Bank z-score is calculated as a weighted average of the z-scores of a country's individual banks (the weights are based on the individual banks' total assets). The Z-score compares a bank's buffers (capitalization and returns) with the volatility of those returns. It captures the probability of default of a country's banking system. Data from WDI.
concentration	Assets of the five largest commercial banks as a share of total commercial banking assets. Measured as a percentage and data obtained from WDI.
regulatory_index	Index of bank regulatory stringency normalized between 0 (no regulation) and 1 (max regulation). The index is computed following Barth et al. (2004), Navaretti et al. (2018), and Cull et al. (2023) using the World Bank's Bank Regulation and Supervision Survey. The regulatory indices are activity restrictions, capital requirements, supervisory power, and ease of entry.

Table A2: Basic Summary Statistics

	N	Mean	Min	Max	SD
FinTech Lending	1024	1423.94	0	356832	15921
BigTech Lending	709	2866.11	0	668819	35170
Alternative Credit	1024	3408.38	0	669973	38666
GDPpc growth	1009	1.03	-30	30	4
GDP per capita	990	22353.94	707	159305	22188
BankBranches	944	16.17	0	77	13
Fincial crisisDummy	1024	0.20	0	1	0
LernerIndex_normalized	672	0.58	0	1	0
dom_private_credit	932	56.27	0	259	43
Provison_npl	669	68.61	13	283	39
dom_credit	242	91.49	14	391	70
bank_credit_private_GDP	916	56.28	1	259	42
Concentration	871	78.53	25	100	16
Non-Performing Loan	718	5.81	0	55	7
Capital adequacy	721	17.86	8	36	4
Z-Score	945	16.97	1	62	10
ROA	945	1.29	-3	13	1
Liquidity	882	32.43	5	107	16
Margin	945	4.23	0	15	3
Comm.bank borrower	527	238.33	1	1167	222
Non-int.income to tot.income	945	38.68	7	92	13
lending_rate	650	11.46	0	67	9
real interest rate	648	6.54	-81	62	11
Mobilesubscrper100people	1010	108.30	13	291	35
broadbandper100pep	984	14.87	0	54	14
fixed_teleper100pep	1003	17.39	0	134	18
Inflation	1009	5.01	-30	605	22
Trade openness	960	85.66	16	426	57
Popln growth.rate	1019	1.28	-5	12	1
Made_received_digtl paymnt	941	0.54	0	1	0
Trust_index	941	0.08	-2	2	1
Bank regulatory_index	969	0.41	0	1	0

Source: Own computation

Table A3: Second Stage IV Regression Robustness check

	Bank Credit	Bank Credit	Bank Credit
Hansen J P-value	0.932	0.867	2.321
Cragg-Donald Weak identification Wald F statistic	17.986	18.162	34.486
Anderson canon. corr. LM Underidentification test	27.315	17.220	31.724
F-statistic P-value	0.000	0.000	0.000

BigTech, FinTech, alternative credit, and conventional bank credit have been winsorized at the 1% and 99% levels. All regressors are lagged and expressed in natural logarithmic form, except BigTech credit (which uses level values in million USD due to zero inflation) and dummy variables. This table reports robustness checks corresponding to Equation 1.2, extending Table 1.2. The dependent variable is conventional bank credit. Columns (1) to (3) examine the relationship between bank credit and, respectively, alternative credit, FinTech credit, and BigTech credit. The sample covers four income groups: high, upper middle, lower middle, and low income (World Bank classification). The Hansen J test evaluates overidentifying restrictions under the null hypothesis that the instruments are exogenous. Failure to reject the null, as observed here, supports the validity of the instruments in all three specifications. The Cragg-Donald weak identification test assesses whether instruments are weak; the results exceed the critical values from Stock-Yogo (9.08 for AC and FinTech, 19.93 for BigTech), confirming that weak identification is not a concern. The Anderson canonical correlation LM statistic tests for underidentification, and its significance (large test values) indicates that the instruments are relevant in the first stage. Finally, the F-statistic confirms that the instruments are jointly significant at the 1% level.

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Second Stage IV Regression with Region FE and Year FE

	(1)Bank Credit	(2)Bank Credit	(3)Bank Credit
Alternative credit	0.070**		
	(0.034)		
FinTech credit		0.065**	
		(0.026)	
BigTech credit			0.688
			(0.676))
ROA	0.044	0.006	-0.362
	(0.033)	(0.031)	(0.604)
margin	-0.143***	-0.119***	-0.209
	(0.018)	(0.018)	(0.156)
Comm.Bank Borrowers	0.001***	0.001***	0.001
	(0.000)	(0.000)	(0.011)
Openness	-0.001	0.187**	2.775
	(0.001)	(0.079)	(2.453)
Bank regulatory index	0.528***	0.591***	2.451
	(0.145)	(0.122)	(2.057)
Bank Branches	0.257***	0.309***	-0.831
	(0.055)	(0.048)	(0.613)
Lerner Index	0.072	0.082	-0.477
	(0.076)	(0.065)	(0.926)
Popln growth rate	-0.002	-0.042	-0.174
	(0.034)	(0.034)	(0.398)
Covid19	-0.499*	-0.590*	-8.113
	(0.272)	(0.333)	(6.644)
Alt.Regulation	-0.041	-0.065	-0.346
	(0.068)	(0.069)	(0.812)
Constant	6.315***	3.459***	-1.130
	(1.098)	(0.460)	(7.707)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Adj.R-squared	0.771	0.792	0.475
Observations	253	272	60
F-statistic P-value	0.000	0.000	0.001
Hansen J test P-value	0.3247	0.4358	0.8964

BigTech, FinTech, AC, and conventional bank credit have been winsorized and at the 1% and 99%. All the regressors are lagged and in natural logarithmic form except for the dummies. This table reports results for Equation 1.2. The dependent variable is conventional bank credit. The table presents the results where I investigate the relationship between conventional bank credit with AC(column 1), FinTech credit(column 2), and BigTech credit(column 3). The sample includes six geographic regions: Africa, Asia Pacific, Europe, Latin America, the Middle East, and North America. F-statistics P-value and Hansen J p values for the instruments used are reported. The null hypothesis of the F-test is that the instruments are weak, while the Hansen test null hypothesis is that the instruments are not correlated with the residuals.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Second Stage IV Regression with Region FE and Year FE on the Total Volume of Credits

	Bank Credit	Bank Credit	Bank Credit
Alternative credit	0.052**		
	(0.025)		
FinTech credit		0.086*	
		(0.047)	
BigTech credit			0.117***
			(0.043)
GDP per capita	-11.675*	-13.257*	5.512
	(6.218)	(7.804)	(5.017)
Bank Branches	17.193***	20.151***	4.039
	(3.395)	(5.781)	(4.167)
Governance indicator	11.469***	11.815*	15.357***
	(4.384)	(6.718)	(4.852)
Real Intrst rate	-0.144**	-0.099	-0.123*
	(0.068)	(0.081)	(0.071)
Covid19	-4.590***	-6.552***	-3.361*
	(0.892)	(1.200)	(1.967)
Data Regulation	-9.307**	-9.753	2.634*
	(4.435)	(6.241)	(1.563)
Popln growth rate	-0.639	-0.535	6.080***
	(0.642)	(0.687)	(1.371)
Bank regulatory index	-2.210	-1.837	-1.056
	(1.799)	(2.204)	(1.006)
ROA	-0.402*	-0.696	1.723**
	(0.236)	(0.549)	(0.790)
Liquidity	-0.125***	-0.084*	0.008
	(0.041)	(0.048)	(0.056)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
IncomeGroup FE	Yes	Yes	Yes
Adj.R-squared	0.483	0.323	0.625
N	465	447	129
F-statistic P-value	0.000	0.000	0.000
Hansen J P-value	0.290	0.516	0.662

BigTech, FinTech, AC, and conventional bank credit have been winsorized and at the 1% and 99%. All the regressors are lagged and in their natural units. This table reports results for Equation 1.2. The dependent variable is conventional bank credit. The table presents the results where I investigate the relationship between conventional bank credit with Alternative credit(column 1), FinTech credit(column 2), and BigTech credit(column 3). The sample includes six geographic regions: Africa, Asia Pacific, Europe, Latin America, the Middle East, and North America. F-statistics P-value and Hansen J p values for the instruments used are reported. The null hypothesis of the F-test is that the instruments are weak, while the Hansen test null hypothesis is that the instruments are not correlated with the residuals. Economic openness and capital ratio were estimated but not reported.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Second Stage IV Regression for High Income Countries

	Bank Credit	Bank Credit	Bank Credit
Alternative credit	0.033**		
	(0.014)		
FinTech credit		0.041**	
		(0.020)	
BigTech credit			2052.358**
			(833.444)
Capital ratio	-0.001	0.006	0.014
	(0.011)	(0.008)	(0.011)
ROA	-0.016	-0.029	0.025
	(0.039)	(0.037)	(0.036)
margin	-0.176***	-0.116*	-0.111**
	(0.052)	(0.059)	(0.048)
Comm.Bank Borrowers	0.001***	0.001***	-0.001*
	(0.000)	(0.000)	(0.000)
Openness	-0.002*	-0.210	0.001
	(0.001)	(0.148)	(0.002)
Bank regulatory index	2.105***	2.228***	2.046***
	(0.566)	(0.630)	(0.555)
Bank Branches	-0.000	0.093	0.016***
	(0.116)	(0.124)	(0.006)
Lerner Index	0.059	0.053	0.350***
	(0.079)	(0.081)	(0.114)
Popln growth rate	0.085*	0.047	0.036
	(0.046)	(0.053)	(0.069)
Covid19	-1.603***	-1.701***	-3.439***
	(0.391)	(0.505)	(0.850)
Constant	4.316***	3.994***	3.266***
	(0.807)	(1.222)	(0.652)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Adj.R-squared	0.836	0.854	0.834
Observations	91	91	61
F-statistic P-value	0.000	0.000	0.000
Hansen J P-value	0.629	0.919	0.171

BigTech, FinTech, AC, and conventional bank credit have been winsorized and at the 1% and 99%. All the regressors are lagged and in their natural units. This table reports results for Equation 1.2. The dependent variable is conventional bank credit. The table presents the results where I investigate the relationship between conventional bank credit with AC(column 1), FinTech credit(column 2), and BigTech credit(column 3). The sample only accounts for the high-income countries based on the World Bank income level group. The sample includes six geographic regions: Africa, Asia Pacific, Europe, Latin America, the Middle East, and North America. F-statistics P-value and Hansen J p values for the instruments used are reported. The null hypothesis of the F-test is that the instruments are weak, while the Hansen test null hypothesis is that the instruments are not correlated with the residuals. Liquidity and dummy for alternative credit regulation are estimated but not reported.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Second Stage IV Regression for Low and Middle-Income countries

	Bank Credit	Bank Credit	Bank Credit
Alternative credit	0.039**		
	(0.017)		
FinTech credit		0.192*	
		(0.115)	
BigTech credit			27.963*
			(16.664)
margin	-0.044**	-0.003	-0.086**
	(0.021)	(0.033)	(0.038)
Comm.Bank Borrowers	0.001***	0.002***	0.001**
	(0.000)	(0.000)	(0.000)
Openness	0.006***	0.885***	0.008***
	(0.001)	(0.279)	(0.002)
Bank regulatory index	0.497***	0.508***	0.565***
	(0.101)	(0.158)	(0.194)
Bank Branches	0.038	0.013	0.000
	(0.062)	(0.083)	(0.006)
Lerner Index	0.140*	0.192**	0.135
	(0.077)	(0.087)	(0.104)
Popln growth rate	0.049	-0.016	-0.013
	(0.044)	(0.060)	(0.052)
Covid19	-0.403***	-0.823**	-0.710**
	(0.136)	(0.352)	(0.312)
Constant	5.004***	2.604***	3.861***
	(0.667)	(0.413)	(0.251)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Adj.R-squared	0.878	0.780	0.836
Observations	162	162	140
F-statistic P-value	0.000	0.000	0.000
Hansen J P-value	0.112	0.220	0.185

BigTech, FinTech, AC, and conventional bank credit have been winsorized and at the 1% and 99%. All the regressors are lagged and in their natural units. This table reports results for Equation 1.2. The dependent variable is conventional bank credit. The table presents the results where I investigate the relationship between conventional bank credit with AC(column 1), FinTech credit(column 2), and BigTech credit(column 3). The sample only accounts for the upper middle income, lower middle income, and low income based on the World Bank income level group. The sample includes six geographic regions: Africa, Asia Pacific, Europe, Latin America, the Middle East, and North America. F-statistics P-value and Hansen J p values for the instruments used are reported. The null hypothesis of the F-test is that the instruments are weak, while the Hansen test null hypothesis is that the instruments are not correlated with the residuals. Capital ratio, ROA, liquidity and Liquidity, and a dummy for alternative credit regulation are estimated but not reported were estimated but not reported.

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Second Stage IV Regression Excluding USA and China

	(1)Bank Credit	(2)Bank Credit	(3)Bank Credit
Alternative credit	0.149*		
	(0.084)		
FinTech credit		0.068***	
		(0.021)	
BigTech credit			0.137***
			(0.039)
GDP per capita	0.208***	0.176***	-0.158
	(0.055)	(0.039)	(4.100)
Bank Branches	0.013	0.157***	-1.357
	(0.093)	(0.028)	(2.466)
Real interest rate	0.007**	0.001	0.388**
	(0.003)	(0.002)	(0.170)
Covid19	-0.511*	0.067	-12.135
	(0.306)	(0.064)	(9.293)
Regulation	-0.191	-0.039	4.544
	(0.135)	(0.064)	(2.774)
Population	-0.016	0.034*	4.244***
	(0.038)	(0.021)	(1.350)
Bank regulatory index	-0.335	-0.043	-2.539
	(0.392)	(0.066)	(10.337)
ROA	-0.058*	-0.043***	0.434
	(0.034)	(0.014)	(2.348)
Liquidity	-0.007***	-0.005***	-0.269**
	(0.002)	(0.001)	(0.118)
Governance indicator	0.182**	0.297***	18.175***
	(0.081)	(0.042)	(3.489)
Constant	7.026***	1.783***	98.681**
	(2.629)	(0.346)	(40.414)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
IncomeGroup FE	Yes	Yes	Yes
Adj.R-squared	0.353	0.656	0.808
N	495	427	223
F-statistic P-value	0.000	0.000	0.000

BigTech, FinTech, AC, and conventional bank credit have been winsorized and at the 1% and 99%. All the regressors are lagged and in natural logarithmic form except for the dummies. This table reports results for Equation 1.2. The dependent variable is conventional bank credit. The table presents the results of the investigation into the relationship between conventional bank credit with Alternative credit(column 1), FinTech credit(column 2), and BigTech credit(column 3). The sample excludes China and the United States to account for their large volume of alternative credit markets. The sample includes six geographic regions: Africa, Asia Pacific, Europe, Latin America, the Middle East, and North America. Capital ratio and Lerner index are estimated but not reported.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Impact of Alternative Credit on the Financial Stability

	(1)	(2)	(3)
Alt. credit	0.069***		
	(0.015)		
FinTech credit		0.002*	
		(0.001)	
Bigtech credit			0.115***
			(0.014)
Data Regulation	0.725**	0.559	0.764**
	(0.276)	(0.344)	(0.296)
Covid19	-1.170***	-1.201***	-1.070***
	(0.211)	(0.206)	(0.244)
Bank Branches	-0.053	-0.043	-0.053
	(0.039)	(0.038)	(0.052)
margin	0.170*	0.154*	0.202**
	(0.089)	(0.088)	(0.097)
NPL provisions	-0.010	-0.016	-0.011
	(0.011)	(0.010)	(0.011)
GDP per capita growth	0.039	0.037	0.056
	(0.033)	(0.033)	(0.042)
Inflation	-0.028	-0.022	-0.021
	(0.018)	(0.017)	(0.019)
Openness	0.009	0.008	0.018
	(0.012)	(0.012)	(0.019)
Concentration	0.014	0.006	0.013
	(0.022)	(0.024)	(0.024)
Constant	15.342***	16.672***	14.430***
	(2.371)	(2.484)	(3.189)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Adj.R-squared	0.135	0.135	0.127
N	512	512	398

The table shows the results of the two-way fixed effects regression for Equation 1.3, with the dependent variable being the Z-score. It provides the outcomes when financial stability is regressed on alternative credit (column 1), FinTech credit (column 2), and BigTech credit (column 3), along with other external control variables. The regressors are lagged and in their natural units. BigTech, FinTech, and alternative credit are volumes in USD millions. The sample includes six geographic regions: Africa, Asia Pacific, Europe, Latin America, the Middle East, and North America.

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Impact of Alternative Credit on the Financial Stability (Accounting for the Lag of Financial Stability)

	(1)	(2)	(3)
Alternative credit	0.009***		
	(0.003)		
FinTech credit		0.010***	
		(0.004)	
BigTech credit			0.000***
			(0.000)
L_zscore	0.049***	0.055***	0.044***
	(0.004)	(0.004)	(0.006)
Covid19	-0.122***	-0.127***	-0.136***
	(0.040)	(0.039)	(0.048)
Bank Branches	0.036	0.024	0.062**
	(0.036)	(0.034)	(0.025)
Domestic Credit	-0.086	-0.127*	-0.028
	(0.072)	(0.077)	(0.089)
margin	-0.073**	-0.060	-0.025
	(0.033)	(0.044)	(0.039)
GDPpc growth	0.001	0.004	0.009
	(0.013)	(0.014)	(0.010)
Inflation	0.001	0.002	0.001
	(0.003)	(0.004)	(0.006)
Governance indicator	0.020	0.071	0.055
	(0.071)	(0.074)	(0.094)
Constant	2.279**	2.472***	2.780**
	(0.905)	(0.898)	(1.345)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Adj.R-squared	0.399	0.436	0.446
N	165	152	109

Notes: The table shows the results of the two-way fixed effects regression for Equation 1.3, with the dependent variable being the Z-score. It provides the outcomes when financial stability is regressed on alternative credit (column 1), FinTech credit (column 2), and BigTech credit (column 3), along with other external control variables and the lag of financial stability. GDP per capita, NPL, concentration, and economic openness were estimated but not reported.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Baseline Second Stage IV Regression for Financial Stability

	(1)Z-SCORE	(2)Z-SCORE	(3)Z-SCORE
Alternative credit	0.024***		
	(0.005)		
FinTech credit		0.028***	
		(0.006)	
BigTech credit			33.275***
			(6.846)
Constant	1.729***	1.738***	1.754***
	(0.048)	(0.047)	(0.060)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
IncomeGroup FE	Yes	Yes	Yes
Adj.R-squared	0.843	0.841	0.793
Observations	757	757	561
CDW Weak identification F statistic	139.022	108.019	38.991
AC Underidentification test	143.716	123.567	76.291
F-statistic	103.717	105.628	74.796
F-statistic P-value	0.000	0.000	0.000
ARW Weak-instrument-robust test	31.533	29.409	48.870
ARW test P-value	0.000	0.000	0.000
Hansen J P-value	0.211	0.334	0.149

All the regressors are lagged and in natural logarithmic form except for the dummies. This table reports results for the Equation 1.4 baseline model with no macroeconomic and banking sector characteristics. The dependent variable is the Z-score. The table presents the results of the investigation into the impact of AC(column 1), FinTech credit(column 2), and BigTech credit(column 3) on financial stability. The sample has been divided into four income level groups: high income, upper middle income, lower middle income, and low income, and six geographical regions: Africa, Asia Pacific, Europe, Latin America, the Middle East, and North America. The Weak identification test (Cragg-Donald Wald(CDW) F and Kleibergen-Paap Wald rk F) under the Ho: the equation is weakly identified. For the model to be significant, I should have better than the stock yoga 10% maximal IV sizes. The 10% max Stock Yoga values are 9.08%, 9.08%, and 19.93 for AC, FinTech, and BigTech credit, respectively. The results are valid as all Cragg-donald F-statistics are above the Stock Yogo values. Weak-instrument-robust inference (Anderson-Rubin Wald test) -Tests of joint significance of endogenous regressors in Equation 1.4. Ho: B1=0 and orthogonality conditions are valid. Validity requires I reject the null, suggesting that the endogenous regressor is significant in explaining variation in the financial stability captured by the Z-score, and the instruments are valid. Hansen J statistic (overidentification test of all instruments) under the null hypothesis, the instruments are not correlated with the residuals. Failing to reject the null hypothesis means the instruments are exogenous and valid(uncorrelated with the error term) in the second stage. For the model to be valid, I should fail to reject the null hypothesis, as in all the cases in columns (1) through (3).

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: First Stage IV Regressions

	(1) FinTech Credit	(2) BigTech Credit	(3) Alt. Credit
Mobile subscriptions	1.269***	0.739**	0.009
	(0.127)	(0.316)	(0.013)
Broadband subscriptions	0.037***	1.799***	0.823***
	(0.012)	(0.552)	(0.091)
GDP per capita	0.000022**	-0.00005	-0.600
	(0.000011)	(0.0002)	(0.460)
Inflation	0.006	-0.635	-0.010
	(0.018)	(0.510)	(0.015)
Bank credit to GDP ratio	0.006	–	-0.009**
	(0.004)		(0.004)
NPL	-0.043	2.117***	-0.021
	(0.029)	(0.684)	(0.019)
Capital ratio	0.109***	1.000	0.075**
	(0.032)	(0.660)	(0.033)
Regulatory index	-0.237	83.926***	-0.776
	(0.659)	(16.088)	(0.601)
Lerner Index	0.832***	4.317	-0.941
	(0.297)	(14.027)	(0.608)
Openess	-0.005**	-0.241***	-0.001
	(0.002)	(0.042)	(0.002)
Concentration	0.039***	-1.550***	-0.006
	(0.009)	(0.257)	(0.009)
covid19	2.185***	37.182*	3.127***
	(0.830)	(19.580)	(0.633)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Income Group FE	Yes	Yes	Yes
Adj. R-squared	0.8555	0.9764	0.8518
Observations	518	428	496

This table presents the first-stage IV regressions for FinTech, BigTech, and Alternative Credit, estimated using two-stage least squares (2SLS). These first-stage results serve as inputs to the second-stage analysis, which examines the impact of alternative credit on financial stability. All regressors are lagged, except for the excluded instruments and dummy variables. The sample covers 145 countries and includes fixed effects for year, region, and income group.

Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Second Stage IV Regression on Financial Stability

	(1)Z-Score	(2)Z-Score	(3)Z-Score
Alternative credit	0.062***		
	(0.012)		
FinTech lending		0.048***	
		(0.008)	
BigTech credit			0.007*
			(0.004)
Inflation	-0.005**	-0.006***	0.001
	(0.002)	(0.002)	(0.008)
Bank credit to private GDP	0.002***	0.001***	0.011***
	(0.000)	(0.000)	(0.002)
Non Performing Loans	0.000	0.004	0.029
	(0.002)	(0.003)	(0.034)
Capital ratio	-0.001	-0.002	0.004
	(0.003)	(0.003)	(0.023)
Bank regulatory index	0.207**	0.182*	-0.340
	(0.105)	(0.107)	(0.558)
Lerner Index	0.045	-0.003	0.004
	(0.059)	(0.029)	(0.397)
Openness	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.002)
Concentration	0.002**	0.001	0.013
	(0.001)	(0.001)	(0.009)
Covid19	-0.432***	-0.430***	-3.240***
	(0.095)	(0.096)	(0.716)
GDP per capita	0.122***	-0.000	-0.000
	(0.042)	(0.000)	(0.000)
Constant	0.214	1.654***	0.512
	(0.412)	(0.101)	(1.142)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
IncomeGroup FE	Yes	Yes	Yes
Adj.R-squared	0.852	0.855	0.976
N	496	518	428
F-statistic P-value	0.000	0.000	0.000

The table reports results for Equation 1.4 baseline model with the addition of exogenous controls. Everything else is similar to Table A11. GDP per capita and governance indicators were estimated but not reported.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: Impact of Alternative Credit and COVID-19 Shock on the Financial Stability

	(1)	(2)	(3)
Alternative credit	0.010***		
	(0.004)		
FinTech Lending		0.014**	
		(0.007)	
BigTech credit			0.391*
			(0.220)
Alt.credits*Covid-19 shock	-0.003		
	(0.004)		
FinTech credits*Covid-19 shock		-0.008	
		(0.011)	
BigTech credits*Covid-19 shock			-0.025***
			(0.009)
Covid19	-0.124**	-0.159*	0.443***
	(0.055)	(0.085)	(0.090)
Bank Branches	0.055**	0.043	-0.118
	(0.021)	(0.049)	(0.128)
Domestic Credit	-0.140	-0.427**	-0.482*
	(0.174)	(0.170)	(0.262)
margin	0.134*	0.036	0.153**
	(0.076)	(0.080)	(0.069)
Non Performing Loan	-0.003	-0.003	-0.043
	(0.006)	(0.007)	(0.106)
GDP per capita	-0.241	-0.106	-0.076
	(0.211)	(0.204)	(0.270)
Inflation	0.002	-0.001	-0.002
	(0.004)	(0.003)	(0.005)
Openness	-0.209**	0.002	-0.180
	(0.094)	(0.002)	(0.141)
Concentration	-0.180	-0.002	-0.111
	(0.148)	(0.002)	(0.165)
Constant	6.832***	5.298**	6.336**
	(2.343)	(2.087)	(2.627)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Adj.R-squared	0.484	0.580	0.517
N	130	126	90

The table shows the results of the two-way fixed effects regression for Equation 1.3. The dependent variable is the Z-score. It provides the outcomes when financial stability is regressed on alternative credit (column 1), FinTech credit (column 2), and BigTech credit (column 3), and their corresponding interaction term with COVID-19 shock. The regressors are lagged and in natural logarithmic form. The sample includes six geographic regions: Africa, Asia Pacific, Europe, Latin America, the Middle East, and North America. Domestic credit, Lerner index, regulatory index, and GDP per capita growth were estimated but not reported. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: Transmission Channels of Covid-19 shocks on the Financial Stability

	(1) ln_zscore	(2) ln_zscore	(3) ln_zscore	(4) ln_zscore	(5) ln_zscore	(6) ln_zscore
Privacy Regulation	0.061*	0.069***	0.074**	0.066*	0.075***	0.067**
	(0.033)	(0.023)	(0.034)	(0.033)	(0.027)	(0.028)
Covid19	0.398***	0.224***	-0.170**	-0.057	-0.145	0.041
	(0.053)	(0.067)	(0.074)	(0.079)	(0.091)	(0.098)
Bank Branches	0.053***	-0.146	0.067***	0.052***	0.034**	0.043**
	(0.018)	(0.101)	(0.021)	(0.018)	(0.014)	(0.021)
margin	0.237***	0.127*	0.110*	0.230***	0.152**	0.150**
	(0.072)	(0.066)	(0.059)	(0.072)	(0.057)	(0.062)
GDPpc growth	0.046**	0.042***	0.023*	0.045**	0.025**	0.031*
	(0.018)	(0.012)	(0.014)	(0.018)	(0.011)	(0.016)
Openness	-0.295***	-0.136	-0.142	-0.272**	-0.251**	-0.240**
	(0.097)	(0.117)	(0.142)	(0.103)	(0.104)	(0.088)
Concentration	-0.237	-0.127	-0.081	-0.241*	-0.188	-0.209
	(0.145)	(0.140)	(0.124)	(0.141)	(0.117)	(0.135)
FinTech credit	0.007					
	(0.004)					
BigTech credit		0.600***				
		(190)				
Alt. credit			0.893*	0.008**	1.476***	1.499***
			(0.467)	(0.004)	(0.394)	(0.473)
GDPpc*Covid19		-0.017***				
		(0.004)				
Domestic credit*Covid19			0.001**			
			(0.000)			
Inflation*Covid19	-0.009*			-0.009*		
	(0.005)			(0.005)		
BankBranches*Covid19					0.004*	
					(0.002)	
Margin*Covid19						-0.024**
						(0.010)
Constant	7.809***	6.617***	4.057**	8.566***	7.756***	6.920***
	(2.308)	(2.149)	(1.789)	(2.298)	(2.443)	(2.497)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R-squared	0.574	0.531	0.426	0.530	0.516	0.492
N	117	95	129	116	128	129

Notes: The table shows the results of the two-way fixed effects regression for Equation 1.3, with the dependent variable being the Z-score. It provides the outcomes when financial stability is regressed on FinTech credit (column 1), BigTech credit (column 2), and alternative credit (column 3), along with other external controls, including COVID-19 interaction with the different forms of alternative credit. The regressors are lagged and in their natural units. BigTech, FinTech, and alternative credit volumes are in USD millions per capita. The sample includes six geographic regions: Africa, Asia Pacific, Europe, Latin America, the Middle East, and North America. Domestic credit and GDP per capita were estimated but not reported. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (Only statistically significant channels are presented)

Table A16: Significant HPJ-FE IV Estimates on Bank Credit

	Alternative Credit	FinTech Credit	BigTech Credit
Alternative Credits	0.0027**	0.0117**	0.0069*
	(0.0037)	(0.0061)	(0.0042)
TBC_{it-1}	0.9609***	0.9435***	0.9442***
	(0.0102)	(0.0117)	(0.0109)
GDP per capita	-0.0003	0.0031	0.0014
	(0.0095)	(0.0082)	(0.0079)
Inflation	0.0009	0.0012	0.0010
	(0.0007)	(0.0008)	(0.0009)
Alt.Credit Share	0.0005	0.0003	0.0004
	(0.0003)	(0.0002)	(0.0003)
NPL	0.0018	0.0016	0.0014
	(0.0019)	(0.0021)	(0.0018)
Capital Ratio	0.0006	0.0004	0.0006
	(0.0018)	(0.0019)	(0.0017)
Regulatory Index	0.0238	0.0193	0.0157
	(0.0401)	(0.0420)	(0.0412)
Lerner Index	0.0018	0.0014	0.0029
	(0.0321)	(0.0297)	(0.0314)
COVID-19	-0.0850***	-0.0782***	-0.0744***
	(0.0001)	(0.0001)	(0.0001)
Constant	0.0249	0.0243	0.0237
	(0.1401)	(0.1392)	(0.1379)
N (Half 1)	200	200	200
N (Half 2)	288	288	288
R^2 (Half 1)	0.961	0.944	0.948
R^2 (Half 2)	0.981	0.962	0.975

This table presents Half Panel Jackknife Fixed Effects (HPJ-FE) IV regression estimates for the effect of alternative credit (column 1), FinTech credit (column 2), and BigTech credit (column 3) on traditional bank credit. Each model uses a two-stage IV estimation split across panel halves.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A17: Significant HPJ-FE Estimates on Financial Stability (Based on FE)

	Alternative Credit	FinTech Credit	BigTech Credit
Alternative Credits	0.0085***	0.0100***	0.0004***
	(0.0030)	(0.0036)	(0.0001)
FS_{it-1}	0.0494***	0.0550***	0.0436***
	(0.0038)	(0.0042)	(0.0057)
COVID-19	-0.1219***	-0.1269***	-0.1355***
	(0.0398)	(0.0393)	(0.0482)
Bank Branches	0.0365	0.0242	0.0624**
	(0.0355)	(0.0343)	(0.0252)
Domestic Credit	-0.0864	-0.1271*	-0.0285
	(0.0723)	(0.0765)	(0.0894)
Interest Margin	-0.0725**	-0.0605	-0.0252
	(0.0335)	(0.0438)	(0.0388)
NPLs	0.0081***	0.0073***	-0.0058
	(0.0018)	(0.0016)	(0.0079)
GDP per capita	-0.0103	-0.0345	-0.0308
	(0.0696)	(0.0675)	(0.0973)
GDP growth per capita	0.0012	0.0042	0.0088
	(0.0132)	(0.0135)	(0.0105)
Inflation	0.0005	0.0021	0.0014
	(0.0033)	(0.0035)	(0.0057)
Openness	-0.0074	0.0379	-0.0098
	(0.0815)	(0.0769)	(0.0955)
Bank Concentration	0.0576	-0.0135	-0.1239
	(0.1481)	(0.1515)	(0.1685)
Governance	0.0195	0.0712	0.0546
	(0.0705)	(0.0745)	(0.0945)
Constant	2.2792**	2.4716***	2.7798**
	(0.9046)	(0.8985)	(1.3448)

This table reports HPJ-FE estimates for financial stability (log Z-score) using alternative credit (column 1), FinTech (column 2), and BigTech credit (column 3). Each coefficient is averaged across first and second panel halves. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are reported in parentheses.

Table A18: Significant HPJ-FE IV Estimates on Financial Stability Based on 2SLS

	Alternative Credit	FinTech Credit	BigTech Credit
Alternative Credits	0.0071*	0.0129**	0.0095*
	(0.0037)	(0.0061)	(0.0042)
FS_{it-1}	0.9815***	0.9679***	0.9730***
	(0.0097)	(0.0113)	(0.0107)
GDP per capita	0.0011	0.0039	0.0007
	(0.0104)	(0.0086)	(0.0081)
Inflation	0.0004	0.0016*	0.0009
	(0.0013)	(0.0009)	(0.0011)
Bank Credit	0.0005	0.0004	0.0004
	(0.0002)	(0.0003)	(0.0002)
NPL	0.0019	0.0012	0.0015
	(0.0019)	(0.0020)	(0.0019)
Capital Ratio	0.0009	0.0010	0.0008
	(0.0015)	(0.0019)	(0.0016)
Regulatory Index	0.0125	0.0221	0.0193
	(0.0372)	(0.0451)	(0.0438)
Lerner Index	0.0036	0.0057	-0.0031
	(0.0270)	(0.0311)	(0.0295)
COVID-19	-0.0895***	-0.0910***	-0.0851***
	(0.0114)	(0.0111)	(0.0108)
Constant	0.0310	-0.0785	0.0123
	(0.1385)	(0.1426)	(0.1312)
N (Half 1)	206	200	200
N (Half 2)	288	288	288
R^2 (Half 1)	0.963	0.943	0.979
R^2 (Half 2)	0.981	0.962	0.975

This table presents Half Panel Jackknife Fixed Effects (HPJ-FE) IV regression estimates for the effect of alternative credit(column 1), FinTech credit (column 2), and BigTech credit (column 3) on financial stability. Each model uses a two-stage IV estimation split across panel halves.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A19: Grouped Fixed Effects Estimation: Impact of Alternative Credit Types on Bank Credit

Variable	Group 0	Group 1	Group 2
AltCredit			
Coefficient	0.0022*	0.0015	0.0009**
FinTech Credit			
Coefficient	0.0020**	0.00006**	0.0006*
BigTech Credit			
Coefficient	-0.0226	0.0002*	0.0001*

This table reports coefficient estimates from Grouped Fixed Effects regressions of conventional bank credit on three types of alternative credit: AltCredit, FinTech credit, and BigTech credit. All models include a lagged dependent variable, GDP per capita, bank branches per capita, real interest rate, capital adequacy, liquidity ratio, regulatory stringency index, and a COVID-19 dummy. Group classifications are based on latent heterogeneity as identified by the GFE estimator, which may reflect differences in income level, digital infrastructure, or financial system development. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A20: GFE Estimates on All Control Variables (Z-score Models)

Model	Variable	Group 0	Group 1	Group 2
AltCredit	AltCredit	0.0013**	0.0013**	0.0001*
	GDP per capita	0.0027	0.0279	-0.0048
	Bank credit to GDP	0.0004**	0.0007*	0.0003
	NPL ratio	-0.0014	0.0008	-0.0004
	Capital ratio	0.0002	-0.0003	-0.0010
	Regulatory index	0.0002	-0.0110	0.0301
	Lerner index	-0.0148	0.0178	-0.0005
	Openness	-0.0001	-0.00002	-0.00003
	Concentration	0.00003	0.0002	-0.0006
	COVID-19 dummy	-0.0750***	-0.1326***	-0.1042**
FinTech	FinTech credit	0.0177***	-0.0016	0.0147***
	GDP per capita	0.0000	-0.0000	0.0000
	Bank credit to GDP	0.0009	0.0007	0.0014***
	NPL ratio	-0.0006	0.0039	0.0078**
	Capital ratio	-0.0057	-0.0039	-0.0026
	Regulatory index	0.1420	0.0476	-0.0738*
	Lerner index	0.0641	-0.0789*	-0.0480
	Openness	0.0003	-0.0005	-0.0002
	Concentration	0.0000	-0.0011	0.0023*
	COVID-19 dummy	1.7744***	0.0000	-0.1540**
BigTech	BigTech credit	0.0022*	0.0003***	0.0012***
	GDP per capita	0.0000	-0.0000**	0.0000
	NPL ratio	0.0039	0.0040	-0.0039
	Capital ratio	-0.0073*	-0.0132**	-0.0086*
	Regulatory index	-0.1220**	0.0401	0.0354
	Lerner index	-0.1586*	0.2193	-0.0194
	Openness	-0.0001	0.0010**	-0.0011*
	Concentration	0.0027	0.0062***	-0.0012
	COVID-19 dummy	-0.3078	-0.0698*	0.0000

This table reports coefficient estimates for all control variables included in the GFE regressions of financial stability. All regressors are lagged by one period except for the dummies. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A21: List of Countries in the Study

Countries			
Albania	Argentina	Armenia	Australia
Austria	Bangladesh	Barbados	Belarus
Belgium	Belize	Benin	Bolivia
Bosnia and Herzegovina	Botswana	Brazil	Bulgaria
Burkina Faso	Burundi	Cambodia	Cameroon
Canada	Chile	China	Colombia
Congo, Dem Rep	Costa Rica	Cote d'Ivoire	Croatia
Cuba	Curacao	Cyprus	Czech Republic
Denmark	Dominican Republic	Ecuador	Egypt, Arab Rep
El Salvador	Estonia	Ethiopia	Finland
France	Gambia, The	Georgia	Germany
Ghana	Greece	Guatemala	Guinea
Haiti	Honduras	Hong Kong SAR, China	Hungary
Iceland	India	Indonesia	Iran, Islamic Rep
Iraq	Ireland	Israel	Italy
Jamaica	Japan	Jordan	Kazakhstan
Kenya	Korea, Rep	Kosovo	Kuwait
Kyrgyz Republic	Lao PDR	Latvia	Lebanon
Lesotho	Liberia	Lithuania	Luxembourg
Madagascar	Malawi	Malaysia	Mali
Malta	Mauritania	Mauritius	Mexico
Moldova	Monaco	Mongolia	Morocco
Mozambique	Myanmar	Namibia	Nepal
Netherlands	New Zealand	Nicaragua	Niger
Nigeria	North Macedonia	Norway	Pakistan
Panama	Paraguay	Peru	Philippines
Poland	Portugal	Puerto Rico	Qatar
Romania	Russian Federation	Rwanda	Saudi Arabia
Senegal	Serbia	Sierra Leone	Singapore
Slovak Republic	Slovenia	Somalia	South Africa
South Sudan	Spain	Sri Lanka	Suriname
Sweden	Switzerland	Syrian Arab Republic	Taiwan
Tajikistan	Tanzania	Thailand	Timor-Leste
Togo	Trinidad and Tobago	Tunisia	Turkey
Uganda	Ukraine	United Arab Emirates	United Kingdom
United States	Uruguay	Vanuatu	Venezuela, RB
Vietnam	Virgin Islands (US)	West Bank and Gaza	Yemen, Rep
Zambia	Zimbabwe.		

Chapter 2: The GDPR Disruption: The Impact of Data Privacy Regulation on the Alternative Credit Market

Abstract

This chapter investigates the effect of data regulation on credit provision by FinTech and BigTech firms, collectively referred to as alternative credit. The analysis leverages the 2018 enactment of the European Union's General Data Protection Regulation (GDPR), which curtailed firms' flexibility in collecting, storing, and utilizing personal data. The study uses a panel dataset covering 45 countries from 2013 to 2020 and employs a difference-in-differences (DiD) approach to identify the causal effect of stricter data regulations on the European alternative credit market. The results show that the introduction of data regulation has a positive and significant impact on FinTech credit, suggesting that data protection regulations can benefit FinTech lenders. However, no significant effect of GDPR on BigTech credit is observed. This may reflect that potential reputational or trust-related benefits from compliance are offset by persistent consumer concerns over data misuse, high compliance costs, and stringent regulatory scrutiny, all of which constrain credit supply. Simultaneously, BigTechs' scale and diversified operations may enable them to absorb regulatory shocks, further dampening any observable impact.

Keywords: Alternative credit, BigTech credit, FinTech credit, Data Regulation, GDPR

1 Introduction

In an era where data is often heralded as the new oil, its misuse raises major concerns for consumers and regulators. Technology firms have occasionally eroded trust by mishandling personal data. In 2019, France's data protection authority fined Google 50 million euros for opaque processing practices and inadequate user consent for targeted advertising[5]. High-profile breaches have intensified these concerns. The infamous Cambridge Analytica scandal exposed how Facebook allowed unauthorized harvesting of 50 million users' data for political profiling. Similar risks span to other sectors. In 2020, British Airways was fined 20 million pounds by the UK's Information Commissioner's Office (ICO) after a breach compromised personal and financial details of 500,000 customers (Information Commission Office, 2020). In another major incident, Marriott International disclosed a 2018 breach that exposed sensitive information—names, contact details, passport numbers—of roughly 500 million guests[6], prompting a 99 million pounds fine from the ICO. These incidents have heightened fears about identity theft, digital fraud, and the risks of unregulated data practices, particularly as technology firms expand into financial services.

This chapter examines how data regulation affects credit provision by these same technology-driven lenders - FinTech and BigTech firms - whose activities collectively form the alternative credit market. Alternative credit includes lending by non-traditional financial intermediaries outside the conventional banking system. FinTech credit covers digital models such as peer-to-peer (P2P) lending, invoice trading, and other marketplace platforms (CCAF, 2021; Claessens et al., 2018), often labeled as debt-based alternative finance (Wardrop et al., 2015). BigTech[7] credit refers to lending by large technology firms whose core business is digital services, but who increasingly offer financial products—typically as a subset of a much broader variety of non-financial operations—either directly or through partnerships with financial institution (Cornelli et al., 2023; Doerr, Gambacorta, et al., 2023; Frost et al., 2019). Together, FinTech and BigTech credit make up what is broadly known as alternative credit.

[5] Source: https://www.edpb.europa.eu/news/national-news/2019/cnils-restricted-committee-imposes-financial-penalty-50-million-euros

[6] Source: https://news.marriott.com/news/2018/11/30/marriott-announces-starwood-guest-reservation-database-security-incident

[7] Notable examples include Ant Financial and Tencent in China, M-Pesa in East and North Africa, Mercado Libre in Latin America, Samsung Pay in Korea, Line and NTT Docomo in Japan, Orange in France and the US, and the payment services of Google, Amazon, Apple, and Facebook.

FinTech and BigTech credit have gained significant traction in Asia, East Africa, India, the United States, and Latin America. China leads in BigTech penetration due to Ant Financial and Tencent, both of which offer a wide range of financial services to consumers and small and medium enterprises (SMEs) (Xie et al., 2016). These platforms are economically relevant in financing small and medium enterprises (SMEs) in China, the US, and the UK. In the US and UK, these platforms extended 15.1% and 6.3% of equivalent bank credit to SMEs in 2018, respectively (Frost, 2020). In Europe, the Middle East, and Latin America, alternative credit remains small but growing. FinTech adoption in European countries like the Netherlands, UK, Germany, Sweden, and Switzerland exceeds the global average (Ernst & Young, 2019).

At the core of the digital finance ecosystem lies the extensive use of personal data (Boissay et al., 2021; Doerr, Gambacorta, et al., 2023). Technology firms collect and process vast amounts of user information from diverse sources. These firms leverage financial and behavioral data using machine learning to tailor credit products, assess creditworthiness, and enhance customer experience. However, this data reliance raises concerns about competition, consumer protection, and privacy, particularly for FinTech and BigTech lenders.

Access to personal data enables more accurate credit scoring, but also carries significant risks. AI and machine learning can infer sensitive traits like gender, race, or religion—even without explicit records—by analyzing geographic data (Carstens, 2018), purchase patterns (Feng et al., 2021), or social media content (Fang et al., 2015). While digital footprints can improve default predictions beyond traditional credit bureau scores (Berg et al., 2020), these models may also enable price discrimination (Philippon, 2019) and highly personalized pricing (Ru & Schoar, 2016). Associated risks include identity theft, reputational harm, and behavioral manipulation that pushes consumers toward products that are against their interests. Data privacy also holds intrinsic value, as individuals may wish to protect personal information regardless of economic consequences.

Data privacy regulation establishes rules for collecting, storing, using, and sharing personal information. It grants individuals control over their information and can restrict firms' ability to exploit data across platforms (Carstens et al., 2021; Petralia et al., 2019). Tighter regulation can reduce efficiency by limiting data sharing, yet it also enhances consumer trust and curtails market concentration by dominant firms (Feyen et al., 2021).

These competing effects create a trade-off: privacy regulation may simultaneously suppress or stimulate the growth of alternative credit, making its net impact an open empirical question.

Building on these concerns, countries have increasingly introduced regulatory frameworks to curb the risks of unrestrained data usage. Approaches to data protection vary across jurisdictions. In the European Union, the General Data Protection Regulation (GDPR), which took effect in May 2018, limits firms' ability to collect and retain personal data and mandates prompt user notification in the event of breaches. Following the GDPR, California enacted the Consumer Privacy Act (CCPA), effective January 2020. However, the United States still lacks comprehensive national legislation. As of 2020, countries such as Japan, Canada, and Australia also had no GDPR-like data privacy regulations.[8]

This study examines the impact of the GDPR on the penetration of alternative credit markets driven by FinTech and BigTech firms. These firms rely on non-traditional, granular data to address information asymmetries, personalize products, and innovate credit scoring models (Berg et al., 2020, 2022). GDPR limits access to such data and raises compliance costs, which may reduce venture capital inflows (Frey & Presidente, 2024; Jia et al., 2018) and lower profits due to operational overheads (Frey & Presidente, 2024), thereby constraining the overall supply of alternative credit. However, the regulation may also generate offsetting demand-side effects. By enhancing consumer control over personal data and mandating transparent governance, GDPR can stimulate trust-driven demand. Established technology firms may reinforce their market dominance by capitalizing on economies of scale and greater resources to absorb compliance costs while adopting privacy-focused branding strategies. The resulting consumer trust derived from such branding (Tang, 2019)could offset broader societal skepticism toward data sharing (L. Chen et al., 2021). These countervailing forces—supply-side constraints versus demand-side trust—make the net impact of GDPR on alternative credit theoretically ambiguous. To resolve this ambiguity, the study applies a quasi-experimental design across 45 jurisdictions between 2013 and 2020 to isolate the causal effect of the GDPR on alternative credit extension.

This study makes several novel contributions to the literature on data regulation and alternative credit markets. First, it is the first to empirically examine the effect of the GDPR on

[8]China, India, Indonesia, Malaysia, Albania, Russia, Bosnia and Herzegovina, Belarus, Moldova, Serbia, Turkey, and Ukraine are countries that do not have tough GDPR-like regulations as of 2020.

the credit market penetration of FinTech, BigTech credit, and alternative credit. In contrast to prior qualitative analyses (Boissay et al., 2021; Carstens, 2018; Feyen et al., 2021; Petralia et al., 2019), this study employs quasi-experimental methods—Difference-in-Differences (DiD) and Synthetic Difference-in-Differences (SDiD)—to identify the causal effect of the GDPR on alternative credit markets. These methods are particularly suited for isolating policy effects, as they compare pre- and post-regulation trends between treated (EU) and untreated (non-EU) markets while accounting for unobserved heterogeneity. DiD serves as the benchmark method due to its clarity, established applicability in regulatory analysis, and the presence of clear treatment assignment, timing, and availability of panel data across treated and control groups, which satisfy the parallel trends assumption. SDiD complements DiD and serves as a robustness check that accounts for potential pre-treatment trend differences through constructing a data-driven synthetic counterfactual, enhancing the credibility of the findings.

Second, the study distinguishes itself through its comprehensive coverage of the alternative credit market. It includes BigTech credit and all digital lending models categorized as FinTech credit by the Cambridge Center for Alternative Finance (CCAF)[9]. This comprehensive approach captures the full spectrum of FinTech and BigTech credit innovations, enabling a robust analysis of how different business models respond to regulatory constraints. Moving beyond narrowly defined segments such as peer-to-peer lending, the study offers a nuanced understanding of privacy regulation's impact on the alternative credit ecosystem, revealing structural and functional dynamics often overlooked in prior studies. This methodological breadth enhances the study's comprehensiveness and ensures its findings reflect the multifaceted nature of digital credit markets, distinguishing it from existing literature. Ultimately, this broader lens delivers policy-relevant insights into how regulatory frameworks shape credit market evolution across institutional and economic contexts.

Third, the analysis leverages a multi-country panel dataset covering 45 jurisdictions—including the European Economic Area, the United States, and other key markets—to assess the impact of data regulation on digital credit markets. This cross-national perspective marks a significant advancement over single-country studies (Doerr, Gambacorta, et al., 2023; Gambacorta et al., 2022, 2024) by capturing cross-national regulatory differences while

[9]CCAF's FinTech credit includes Balance Sheet Lending (Business, Property, and Consumer), P2P / Marketplace Lending (Consumer, Business, Property), Debt-Based Securities, Mini-Bonds, and Invoice Trading.

controlling for fixed country characteristics, strengthening causal identification and generalizability. Its broad geographic scope increases variation in regulatory exposure and market conditions, improving estimate precision and enabling detection of nuanced policy effects. This approach also reduces country-specific biases and allows cross-country comparisons, revealing how institutional and economic contexts shape the effectiveness of data privacy laws.

Finally, while prior work has examined the drivers of alternative credit growth (Cornelli et al., 2020, 2023; Frost et al., 2019, 2020) or focused narrowly on settings like US mortgage lending under the CCPA (Doerr, Gambacorta, et al., 2023), this study is the first to quantify how the GDPR reshapes the aggregate supply of alternative credit across jurisdictions and time. In doing so, it provides new empirical evidence on the regulatory trade-offs between consumer data protection and financial innovation.

The results show that FinTech credit increased by 1.31 percentage points following the introduction of GDPR, likely driven by enhanced consumer trust and increased engagement with digital platforms. When combined with mobile infrastructure, this trust reinforces the data-network-activity (DNA) loop, enabling FinTech firms to attract users, refine analytics, improve service quality, and scale credit provision.

In contrast, the impact on BigTech credit is more subdued and uneven, likely reflecting the heavier compliance obligations and unresolved concerns about data exploitation. The regulation's effectiveness is further shaped by country-specific institutional environments. High levels of public trust enhance the GDPR's effect, underscoring the role of institutional legitimacy in fostering sustainable digital lending. Although market concentration generally limits the regulation's reach—especially in systems dominated by incumbents—market power, reflected in pricing flexibility, appears to amplify the regulation's positive influence on credit expansion. These dynamics indicate that FinTechs are structurally positioned to capitalize on privacy-oriented reforms, while BigTechs remain constrained by scale-related vulnerabilities and reputational frictions.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 outlines the institutional context of the GDPR and formulates the research hypotheses. Section 4 describes the data sources and empirical methodology. Section 5 presents the main results and robustness checks, and Section 6 concludes with a discussion of policy implications.

2 Literature Review

A growing body of research explores the intersection of data privacy, digital credit innovation, and the evolving role of regulation in FinTech and BigTech lending markets. Acquisti (2023) defines privacy as control over access to personally identifiable information—a concept increasingly valued in the digital era. Privacy concerns are especially pronounced in sectors that rely heavily on data, such as FinTech and BigTech credit markets (Beke et al., 2018). Empirical evidence highlights that consumers place significant value on privacy and express concern over potential misuse or unauthorized access to personal data (Doerr, Frost, et al., 2023; Tang, 2019). Globally, 78% of individuals report at least moderate concern about online privacy, and over half have become more worried in recent years (Simpson, 2019). Survey data from Fazlioglu (2021) show that 68% of consumers globally are either somewhat or very concerned about online privacy. In the United States, Armantier et al. (2021) find that more than 75% of consumers express serious concern over data sharing, citing risks related to identity theft, misuse of personal information, safety, and reputational harm.

While consumers generally value privacy, their willingness to share data is highly context-dependent, shaped by the type of information involved and the perceived benefits of disclosure (Acquisti et al., 2015). Many individuals underestimate privacy risks or lack a full understanding of data practices, which can distort their valuation (S. Barth & De Jong, 2017). Cultural and demographic factors further influence privacy preferences: Boissay et al. (2021) report that 65% of Indian respondents were willing to let banks share their data for better services, compared to only 13% in the Netherlands (S. Chen et al., 2023; Park, 2013). Consumers derive utility from retaining control over personal data; for instance, Tang (2019) find that loan applicants experience satisfaction when withholding information to protect their privacy. Nonetheless, Doerr, Gambacorta, et al. (2023) show that consumers generally prefer to keep their data private.

Two strands of literature examine the implications of emerging credit scoring models. The first highlights their role in enhancing financial inclusion and reducing credit costs through the use of alternative data—such as digital footprints (Berg et al., 2020), platform purchasing behavior (Feng et al., 2021), social media activity (Fang et al., 2015), and communication metadata (Cornelli et al., 2022). By incorporating this information, technology firms can more accurately assess default risk, enabling some borrowers previously deemed subprime to access lower-cost credit (Gambacorta et al., 2024; Jagtiani & Lemieux, 2019). Machine learning and AI-based credit models outperform traditional scores by capturing non-linear patterns, often using simple, widely available digital variables (Albanesi & Vamossy, 2019; Bazzana et al., 2024; Gambacorta et al., 2022; Moscatelli et al., 2020). Combining standard credit bureau data with alternative scoring enhances predictive power (Bazzana et al., 2024; Gambacorta et al., 2024).

The second strand raises ethical and regulatory concerns. Despite superior risk forecasting, these models may intensify price discrimination and entrench inequality (Fuster et al., 2022; Gambacorta et al., 2024). For instance, Fuster et al. (2022) show that Black and Hispanic borrowers benefit less from machine learning-based scores. Algorithmic decision-making may also embed social biases, exacerbating disparities in access and pricing (O'neil, 2017). Garratt and Oordt (2021) warns that, in the absence of privacy-enhancing strategies, firms may exploit behavioral data to segment consumers and extract surplus, leading to socially inefficient outcomes. Evidence also points to widespread violations of data privacy norms, such as the unauthorized sharing of sensitive medical data by major UK health websites with global advertising and data brokerage firms (Murgia & Harlow, 2019).

These underline challenges the need for comprehensive data governance. Fragmented regulatory approaches, such as those in the United States, offer firms broad access to personal data, potentially enabling exploitative practices (Boissay et al., 2021). By contrast, unified frameworks like the EU's GDPR shift control over data to individuals. Doerr, Gambacorta, et al. (2023) find that privacy regulation under the California Consumer Privacy Act increased consumer trust, particularly in FinTech firms, resulting in higher loan application volumes and improved credit pricing through enhanced data sharing.

Several studies have examined the evolution and implications of alternative credit markets. However, this paper differs from prior work by analyzing how data privacy regulation affects the development of FinTech and BigTech credit. Despite the growing significance of regulatory frameworks for these sectors, limited empirical research exists on the regulatory impact—particularly across countries. Most prior studies focus on the determinants of FinTech or BigTech credit individually, often emphasizing market-level or institutional drivers. Others explore related themes such as credit composition, financial stability, and privacy–competition trade-offs. These contributions are reviewed below.

Gambacorta et al. (2022) analyze the Chinese BigTech credit market, showing that lending volumes are more responsive to firm-level characteristics—such as transaction frequency and network centrality—than to macroeconomic indicators or collateral values. Similarly, Frost et al. (2019) investigate BigTech lending through case studies of Mercado Libre (Argentina) and Ant Financial (China), finding that economic activity, competition, and regulatory conditions shape BigTech credit dynamics. Their study highlights the informational advantage BigTech firms hold in credit scoring relative to traditional lenders. At the micro level, Gambacorta et al. (2024) use AliPay loan data and show that alternative data sources enhance predictive accuracy, especially in periods of aggregate credit contraction.

Broadening the scope, Cornelli et al. (2020) employ panel regressions across 79 countries (2013–2018) and show that FinTech and BigTech credit expand where credit demand is underserved and entry conditions are favorable. Key drivers include GDP per capita, banking sector markups, regulation, branch network density, and digital infrastructure. Haddad and Hornuf (2019) further identify macro-financial enablers—such as access to finance, venture capital availability, secure internet access, and mobile phone penetration—as important for alternative credit market growth.

Several qualitative studies, including Boissay et al. (2021), Carstens (2018), Feyen et al. (2021), and Petralia et al. (2019), emphasize the dual role of FinTech and BigTech lenders in expanding financial access while raising new policy concerns. These include the risk of price discrimination, algorithmic bias, anti-competitive practices, and the exploitation of personal data. However, such studies often limit their scope to peer-to-peer lending and do not empirically test the effects of regulatory shifts on alternative credit markets.

Recent empirical work by Doerr, Gambacorta, et al. (2023) examines the California Consumer Privacy Act (CCPA) and its effect on mortgage lending by FinTech firms in the US, showing that stronger privacy regulation can enhance consumer trust and credit uptake. While valuable, such studies remain country-specific. In contrast, cross-country analyses—such as those by Cornelli et al. (2020, 2023) and Frost et al. (2019, 2020)—shed light on broader determinants of FinTech and BigTech credit penetration but do not address the role of regulatory shocks. This paper contributes to the literature by filling this gap, offering a cross-country assessment of how comprehensive data protection frameworks—such as the GDPR—shape the evolution of alternative credit.

3 GDPR Institutional Framework and Research Hypotheses

The General Data Protection Regulation (GDPR) represents one of the most comprehensive and far-reaching data privacy frameworks enacted to date. Adopted by the European Union in 2016 and enforced from May 25, 2018, the GDPR establishes unified standards for how personal data is collected, processed, and stored across all EU member states.[10] It replaces the earlier 1995 Data Protection Directive, providing stronger enforcement tools and broader individual rights, including the rights to data access, rectification, erasure, and portability. Its jurisdiction extends beyond EU borders to include any entity offering goods or services to EU residents, regardless of location.

The regulation imposes substantial penalties for non-compliance—up to €20 million or 4% of a firm's global revenue, whichever is greater. Although enforcement was initially limited, both the volume and severity of fines have increased markedly in recent years. Total GDPR-related penalties rose from €172 million in 2020 to over €2.1 billion by 2023, with the number of fines also growing significantly.[11] Despite its harmonized legal framework, GDPR enforcement exhibits variation across countries, with differences in interpretation, fine severity, and regulatory prioritization (Wolff & Atallah, 2021).

From an institutional standpoint, the GDPR introduces a trade-off for firms operating in data-intensive sectors. On the one hand, it enhances consumer trust by increasing transparency and giving individuals greater control over their personal data. Individuals will know which data they provide and have control over it. This creates a trustworthy company-client relationship and build confidence and bring more product or service choices for customers. On the other hand, the compliance burden—both legal and technological—can be significant. Firms must implement data management systems, conduct audits, and ensure secure consent mechanisms, among other obligations. For early-stage and small firms, these requirements may impose disproportionate costs, potentially deterring market entry and innovation (Frey & Presidente, 2024; Jia et al., 2018).

These dynamics are particularly relevant for alternative credit providers—namely FinTech and BigTech firms—that rely on digital data to assess borrower risk and deliver credit outside traditional banking channels. Such firms utilize non-traditional information sources, including transaction patterns, mobile usage, social media activity, and behavioral signals,

[10]Source: https://gdpr.eu/what-is-gdpr/
[11]Source: https://www.statista.com/chart/30053/gdpr-data-protection-fines-timeline/

to generate credit scores. While the GDPR may enhance the legitimacy and trustworthiness of these firms by clarifying data usage practices, it also risks constraining their operational models by limiting access to granular personal data or increasing compliance complexity.

BigTechs often possess the financial, technological, and legal infrastructure necessary to absorb compliance costs and adapt quickly to regulatory shifts, and thus GDPR may serve as a competitive advantage. These firms Conversely, smaller entrants may face significant barriers, including reduced venture capital access and lower operational flexibility (Geradin et al., 2021; Wolff & Atallah, 2021). Indeed, empirical evidence indicates that GDPR adoption coincided with a decline in VC funding to smaller EU-based technology firms, and increased R&D and legal expenses among digital platforms (Frey & Presidente, 2024; Jia et al., 2018).

From the consumer perspective, privacy-related discontent has been mounting. Concerns over price discrimination, behavioral profiling, and data misuse have led to greater skepticism toward digital platforms, particularly among BigTech providers (Bian et al., 2023; L. Chen et al., 2021; Goldfarb & Tucker, 2012; Tang, 2019). As such, the overall impact of the GDPR on alternative credit is theoretically ambiguous: while it may boost user trust and legal certainty, it could simultaneously suppress credit supply by increasing entry barriers and constraining data access.

To empirically examine these competing forces, this study formulates the following hypotheses:

Hypothesis 1: Impact of GDPR on Alternative Credit

The GDPR introduces a structural trade-off for alternative credit markets. Strengthening data rights may enhance consumer trust and encourage engagement with compliant digital lenders (Berg et al., 2022; Frey & Presidente, 2024). In the long run, GDPR compliance may also reduce uncertainty and litigation risk by providing a clearer regulatory framework for data governance (Almeida Teixeira et al., 2019; Leuz & Wysocki, 2016). At the same time, increased compliance burdens may suppress innovation, reduce profitability, and deter new entrants (Frey & Presidente, 2024; Jia et al., 2018). Persistent consumer mistrust—especially toward BigTechs—may further dampen the regulation's trust-enhancing effect (Bian et al., 2023; L. Chen et al., 2021; Tang, 2019). As a result, the net effect of the GDPR on alternative credit remains theoretically ambiguous. If compliance-related burdens prevail, alternative credit penetration are expected to decline post-GDPR. Conversely, if trust-enhancing effects dominate, the regulation may stimulate greater uptake and expansion in the alternative credit market.

Hypothesis 2: Differential Effects of GDPR on FinTech and BigTech Credit

The impact of GDPR is likely heterogeneous across digital credit providers. FinTech firms may benefit from improved institutional transparency and data protections, which could foster consumer trust and increase credit uptake. By contrast, the impact on BigTech credit remains less predictable. BigTech firms possess the financial capacity, technological infrastructure, and legal expertise to meet GDPR obligations with minimal operational disruption. These advantages position them to absorb compliance costs efficiently. Yet, these firms face elevated regulatory scrutiny and persistent public skepticism regarding their data practices. As a result, any operational resilience may be counterbalanced by reputational and policy-related headwinds that limit trust-building and constrain credit growth. Thus, the net effect on BigTech credit hinges on whether compliance-driven operational advantages outweigh reputational frictions and intensified oversight.

Hypothesis 3: Effect of GDPR Enforcement Intensity on Alternative Credit

Legislative enactment alone does not guarantee behavioral change; such change typically follows from credible, visible, and sustained enforcement. The regulatory compliance literature highlights that credible and sustained enforcement is often necessary to instill institutional trust and compliance (Almeida Teixeira et al., 2019; Bhattacharya & Daouk, 2002; Leuz & Wysocki, 2016). This study hypothesizes that the impact of GDPR on alternative credit provision depends on the strength of enforcement. In jurisdictions with more robust enforcement regimes, the regulation is expected to enhance legal certainty, reduce data-related risks, and promote digital credit expansion. Where enforcement is weak or inconsistent, these benefits may fail to materialize.

Hypothesis 4: Structural and Institutional Heterogeneity

The effect of GDPR is also expected to vary based on country-specific structural conditions. Following Bazarbash (2019), Claessens et al. (2018), Cornelli et al. (2023), and Frost et al. (2019), the study incorporates several macro-financial and institutional covariates. Higher GDP per capita is associated with increased credit demand, though at a diminishing rate—captured by a negative coefficient on the squared term. Fewer bank branches per capita indicate limited physical access to traditional finance and may boost demand for digital credit. Stricter banking regulations may deter alternative lenders, while stronger governance quality enhances regulatory trust. Inflation, as a proxy for macroeconomic instability, may increase the appeal of non-bank lending. Greater consumer trust in technology firms is also expected to facilitate credit adoption. Higher banking sector mark-ups, reflecting costlier incumbent services, are expected to increase FinTech and BigTech lending as borrowers seek more affordable alternatives. Lastly, in highly concentrated banking systems, GDPR may reinforce incumbent dominance and hinder the growth of digital credit; in more competitive environments, it may level the playing field and promote alternative credit expansion (Gal & Aviv, 2020; Geradin et al., 2021; Johnson, 2022).

4 Data, Empirical Framework and Methodology

This section begins by detailing the main variables and data sources employed in the analysis. It then presents a set of descriptive statistics and stylized facts to provide preliminary insights into the data. The discussion proceeds to outline the empirical strategy used to estimate the impact of data protection regulation on alternative credit markets. Finally, it describes the alternative model specifications and robustness checks designed to validate the findings.

4.1 Data and Variable Description

The empirical analysis is based on a panel dataset comprising annual observations for 45 countries from 2013 to 2020. The dependent variable is alternative credit, defined as the combined volume of FinTech and BigTech lending, both of which operate outside traditional banking institutions. These credit volumes are expressed in U.S. dollars per capita. FinTech credit reflects credit activity by nonbank digital financial intermediaries and includes peer-to-peer lending, marketplace loans, invoice trading, and other platform-based credit mechanisms. These data are sourced from the Global Alternative Finance Database, curated by the Cambridge Center for Alternative Finance (CCAF), which compiles structured survey responses, web-scraped financial data, and institutional collaborations with academic and research partners.

BigTech credit refers to loan provision by large digital conglomerates whose core business lies outside the financial sector but who integrate credit into their broader digital ecosystems. Examples include firms such as Ant Group, Tencent, Amazon, and M-Pesa. Data on BigTech credit are obtained from the cross-country datasets assembled by Cornelli et al. (2023) and Frost et al. (2019) based on various publicly available sources and the firm's annual reports. While FinTech platforms typically operate as standalone intermediaries, BigTech credit is embedded within multifunctional digital platforms, where lending is offered alongside services such as e-commerce, payments, and cloud infrastructure.

To disentangle the effect of GDPR on alternative credit provision relative to overall credit activity, the analysis also examines alternative credit as a share of total credit. This ratio captures compositional shifts in credit allocation and reveals whether GDPR disproportionately expands digital credit channels compared to traditional ones. Since GDPR may plausibly influence both alternative and conventional lending markets, it is essential to evaluate changes in their relative magnitudes. Accordingly, the study additionally estimates models using total credit and alternative credit as a share of total credit as dependent variables.

Total credit is defined as the sum of traditional bank credit and alternative credit, aggregated at the country-year level and expressed in constant U.S. dollars per capita. To account for scale differences, consistency across estimations, and mitigate skewness, the variable is transformed into natural logarithms. Traditional bank credit reflects the volume of credit extended by commercial banks to the private sector. This measure excludes nonbank credit and is sourced from the World Bank's World Development Indicators (WDI).

The key policy variable is the General Data Protection Regulation (GDPR), enforced across European Economic Area (EEA) countries beginning in 2018. For empirical purposes, the GDPR is modeled as a binary treatment indicator equal to one for EEA countries and zero otherwise. This uniform treatment assignment enables a quasi-experimental research design to evaluate the causal effect of GDPR on FinTech credit, BigTech credit, and their combined measure, alternative credit.

In line with prior research demonstrating that enforcement activity—rather than the mere existence of legal frameworks—drives institutional trust and behavioral change (Bhattacharya & Daouk, 2002; Leuz & Wysocki, 2016), this study constructs a continuous measure of regulatory compliance intensity. The Compliance Enforcement Intensity (CEI) index captures annual country-level variation in GDPR enforcement across EEA jurisdictions. Drawing from the Enforcement Tracker database[12], the CEI index combines two dimensions: (i) the total number of GDPR-related fines issued in a given year (Enforcement Frequency) and (ii) the total monetary value of these fines (Enforcement Severity). The first reflects legal activity and regulatory vigilance, while the second proxies for institutional strength and deterrent credibility.

The original dataset records each fine by its exact issuance date. To construct the panel variable, enforcement events are aggregated by country and year. Logged versions of both components are used to address skewness and mitigate the influence of outliers. A composite index is then generated to jointly capture the scale and intensity of enforcement as in Jackson and Roe (2009).

[12] https://www.enforcementtracker.com/

To account for heterogeneity in the impact of GDPR across countries with varying credit market structures, the analysis incorporates two complementary measures of banking sector dominance. First, to measure banks' ability to set mark-ups over marginal cost, this study uses the Lerner Index from the World Bank Global Financial Development Database (GFDD), a standard behavioral indicator of market power. The index ranges between 0 and 1, with values closer to 0 indicating near-perfect competition and values closer to 1 reflecting monopoly-like conditions. However, GFDD data are only available up to 2014. To ensure balanced panel coverage through 2020, I extend the series following the methodology of Igan et al. (2021). Specifically, an ordinary least squares (OLS) regression is estimated using observed Lerner values from 2011–2014 and a cyclical mark-up proxy developed by Igan et al. (2021). The resulting coefficients are then used to generate predicted values for the remaining years. The full series is normalized to maintain consistency and comparability across time and countries.

The inclusion of the Lerner Index is analytically important for two reasons. First, it reflects structural features of the domestic banking environment—namely, the degree of pricing power held by incumbent banks—which may affect both credit supply conditions and the demand for nonbank alternatives. In markets where banks exert substantial pricing power, borrowers may face tighter credit conditions, such as higher interest rate spreads or limited credit access, increasing the appeal of FinTech and BigTech credit providers. Second, variation in banking market power may shape the regulatory transmission channel: GDPR's effectiveness in shifting alternative credit flows could differ depending on the extent of dominance exercised by traditional lenders.

To complement this metric, I also include a concentration indicator: the five-bank asset share, which measures the proportion of total banking assets held by a country's five largest banks. This indicator, also sourced from the World Bank GFDD, is widely used in cross-country studies to approximate market concentration. Including both the Lerner Index and the five-bank asset share allows for a more nuanced characterization of competitive dynamics in the financial system.

To capture cross-country variation in the regulatory environment, I construct a composite index of banking regulatory stringency using data from the World Bank's Bank Regulation and Supervision Survey (BRSS). The approach follows the methodology proposed by J. R. Barth et al. (2004), Cull et al. (2023), and Navaretti et al. (2018). Four dimensions of regulatory policy are incorporated: restrictions on banking activities, capital stringency, supervisory power, and barriers to market entry.

The first component, banking activity restrictions, reflects the extent to which banks can undertake securities trading, insurance underwriting, real estate investment, or ownership of non-financial firms. This index ranges from 1 to 12, with higher values indicating tighter restrictions. The second component, capital requirements, combines the rigidity of initial capital sources and the comprehensiveness of capital adequacy rules. Scores range from 0 to 8, where higher values indicate more stringent requirements. These include whether regulators permit using borrowed funds or non-cash assets as capital and whether risk exposures and potential losses are incorporated into capital calculations. Supervisory power indicates whether supervisory authorities possess the legal mandate to undertake specific preventive and corrective actions. This index ranges from 0 to 14, with higher values reflecting stronger and more autonomous supervisory capacity. Lastly, ease of Entry captures the procedural burden of initiating banking operations. It reflects whether more than one license is required to conduct banking activities and the number of regulatory approvals foreign banks need to establish subsidiaries.

Following Cull et al. (2023), these four sub-indices are standardized and aggregated into a single normalized score, ranging from 0 (no regulatory stringency) to 1 (maximum stringency). The resulting composite index offers a parsimonious yet multidimensional measure of the regulatory landscape. Its inclusion in the empirical model enables the analysis to account for institutional frictions that may shape the structure, evolution and cross-country variation of alternative credit markets.

To approximate consumers trust in digital financial services, I construct a behavioral trust index using indicators from the World Bank's Global Findex database. In the absence of direct country-level measures of perceived trust in FinTech and BigTech lenders, I rely on actual user engagement as a proxy. Specifically, the index averages three indicators for individuals aged 15 and above: (i) those who made or received a digital payment, (ii) those who made a digital merchant payment for an online purchase, and (iii) those who used a mobile phone or the internet to make a purchase. The resulting measure is normalized to range between 0 and 1, with higher values interpreted as greater behavioral confidence in digital platforms.

This behavioral interpretation aligns with recent research linking trust, privacy regulation, and digital engagement. Boissay et al. (2021) argue that privacy regulation enhances user trust, triggering a data-driven growth cycle—referred to as the DNA loop—where increased data availability improves service quality, attracts more users, and reinforces platform dominance. Doerr, Gambacorta, et al. (2023) show that privacy protections raise individuals' willingness to share data with digital credit providers, particularly in minimally regulated jurisdictions. Complementing this, Armantier et al. (2021) find that consumers place greater trust in traditional banks than in FinTech or BigTech firms when managing personal data, suggesting that engagement with nonbank platforms depends heavily on perceived data security. These findings collectively support the use of digital engagement as a proxy for trust, reflecting demand-side confidence in the digital credit ecosystem. The constructed trust index captures users' willingness to interact with digital financial platforms and helps explain variation in the diffusion of alternative credit services.

The model includes several structural controls that capture the enabling conditions for alternative credit provision. The first is the number of bank branches per 100,000 adults, which proxies the accessibility of conventional financial services. Countries with fewer physical bank branches tend to exhibit higher demand for non-traditional credit channels, as FinTech and BigTech platforms often step in to fill service gaps. The data are sourced from GFDD, with annual coverage harmonized across countries.

Second, the models account for GDP per capita growth, a key macroeconomic indicator influencing credit demand and repayment capacity. Rapid income growth is typically associated with increased household and firm-level creditworthiness, thereby expanding both traditional and alternative credit markets. Lastly, two variables— mobile phone subscriptions and broadband internet penetration (per 100 people)—are included to capture the digital infrastructure necessary for technology-enabled credit delivery. These are drawn from the International Telecommunication Union (ITU) and the World Development Indicators (WDI), and are log-transformed to reduce skewness. Empirical studies such as Cornelli et al. (2020), Doerr, Gambacorta, et al. (2023), and Hodula (2022) highlight the importance of digital connectivity in scaling both FinTech and BigTech lending models. Summary descriptions of all variables and their sources are provided in Table B1, while Table B2 reports the corresponding descriptive statistics.

4.2 Descriptive Statistics and Stylized Facts

This subsection presents key patterns and trends in alternative and total credit market features, based on summary statistics and visual analysis. The final sample comprises 360 observations across 45 countries from 2013 to 2020. Table B2 reports descriptive statistics for the main outcome and control variables.

The volume of FinTech credit exhibits substantial cross-country dispersion. China leads in absolute terms, with FinTech lending peaking at USD 357 billion in 2017, followed by the United States with USD 71.6 billion. BigTech credit also shows strong geographic concentration. China dominates the landscape, reaching an annual volume of USD 669 billion, far exceeding all other jurisdictions. Average annual lending volumes across the full sample are USD 3.95 billion for FinTech, USD 8.12 billion for BigTech, and USD 9.41 billion for total alternative credit.

Table B3 presents a balance test comparing treated (EEA countries) and control groups prior to the GDPR intervention. Before 2018, the average FinTech lending volume was USD 414 billion in the treatment group (EEA countries) and USD 233 billion in the control group. However, a t-test shows that these differences are not statistically significant, indicating that FinTech activity was relatively balanced across groups prior to treatment. In contrast, there were statistically significant level differences in BigTech credit.

Among control variables, GDP per capita, inflation, real interest rates, bank branch density, broadband internet subscriptions, and governance indicators appear balanced across treatment and control groups in the pre-treatment period. However, several variables show significant baseline differences. The Lerner Index—capturing bank market power—is significantly higher in treated countries, possibly reflecting more concentrated banking systems in the EU. Similarly, the consumer trust index and the level of conventional bank credit also differ between groups before the GDPR came into force. These differences highlight the need for the inclusion of time-varying controls, country and year fixed effects, and alternative estimation strategies. While several baseline differences exist between treated and control groups—particularly in banking market power, consumer trust, and conventional credit—these do not in themselves violate the DiD identification strategy. The critical assumption remains that, absent GDPR, the trends in alternative credit would have evolved similarly across groups, as confirmed by the parallel trends assumption both graphically and through placebo regressions.

Figure 2.1 shows GDPR familiarity levels across countries in 2020, based on Google Trends data measuring search interest in the term "GDPR." Public awareness had reached high levels across most EEA member states, with robust interest in Western and Northern Europe and notable engagement in China. This widespread familiarity supports the interpretation of GDPR as a behaviorally salient and market-relevant regulatory shock, indicating that the regulation has become publicly embedded and potentially influential for consumer trust, platform compliance behavior, and the evolution of alternative credit markets.

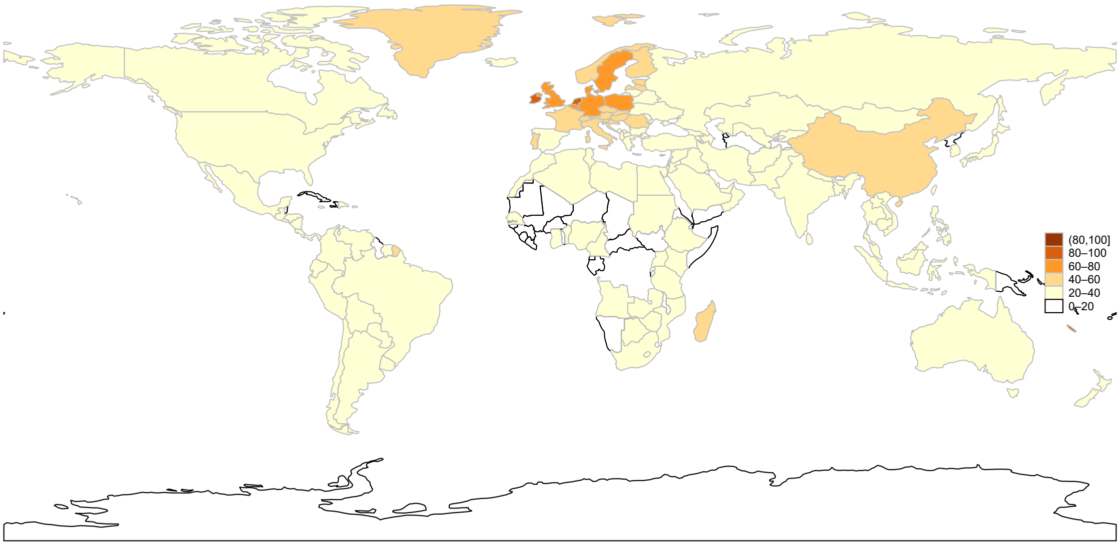

Figure 2.1: Global Google Searches on "GDPR"

Figure 2.2 provides complementary views of the scale and evolution of alternative credit in relation to total domestic credit. It shows that while alternative credit has grown since 2013, it remains a small component of formal credit markets, not exceeding 2% of total domestic credit. FinTech credit initially dominated the alternative credit landscape, with BigTech expanding rapidly after 2016. Despite this growth, the overall footprint of alternative credit remains limited, even though it plays a larger role in digitally advanced but financially underserved economies.

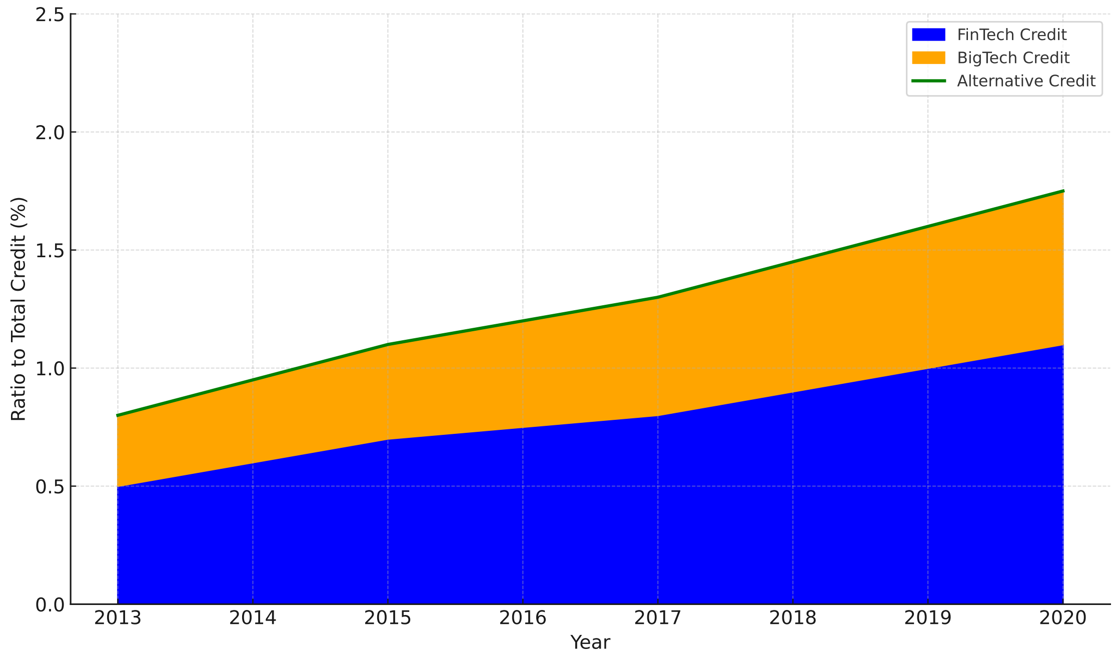

Figure 2.2: Trends in the credit market

Figure 2.3 compares aggregate FinTech and BigTech credit volumes before and after the enforcement of the GDPR in 2018. The results indicate that both segments expanded in the post-GDPR period; however, the increase in BigTech credit was substantially larger. This asymmetry may reflect underlying differences in firms' ability to absorb compliance costs or adapt to regulatory constraints. BigTech platforms—already integrated across digital ecosystems—may have leveraged existing user data and infrastructure to maintain scalability, while FinTech firms expanded at a slower pace, potentially constrained by greater reliance on third-party data flows and more limited operational scale.

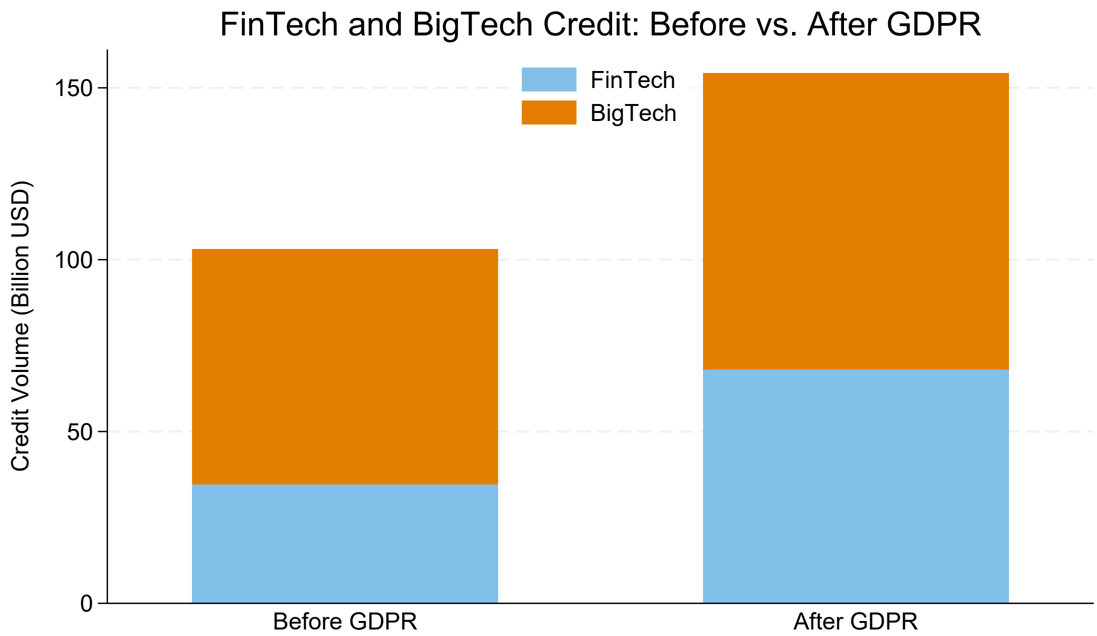

Figure 2.3: FinTech and BigTech Credit: Before vs. After GDPR

Figures 2.4 and 2.5 illustrate the substantial heterogeneity in GDPR noncompliance fines across EEA countries. Figure 2.4 shows that between 2018 and 2020, the cumulative monetary value of the leading ten countries' fines ranged from under 1 million euros in countries like Norway to over 70 million euros in Italy. France, the United Kingdom, and Germany also appear among the top enforcers by total fine value, each exceeding 38 million euros. In contrast, Figure 2.5 ranks countries by the number of fines issued, with Spain leading at 171 cases, followed by Germany (50), Romania (47).

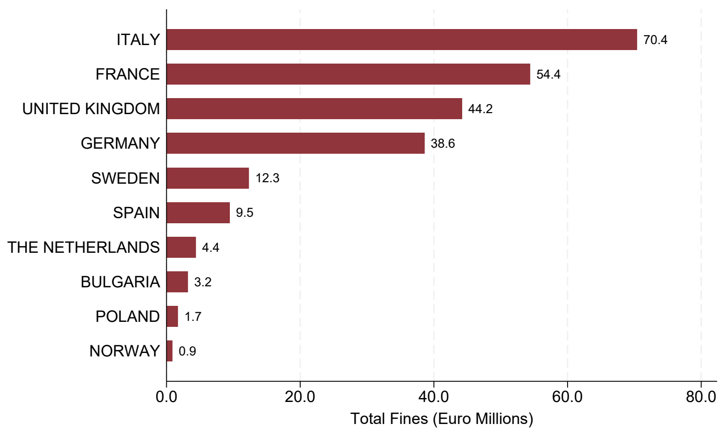

Figure 2.4: Leading 10 EEA Countries by Total Value of GDPR Fines Issued (2018–2020)

Between 2018 and 2020, the number of fines issued per country in a year ranged from as low as 1 to as high as 133, and the corresponding total monetary value ranged from 500 euros to over 58.9 million euros. In total, 561 fines were recorded across the sample, amounting to approximately €245 million in GDPR-related penalties. These figures illustrate the substantial variation in both enforcement frequency and severity across jurisdictions.

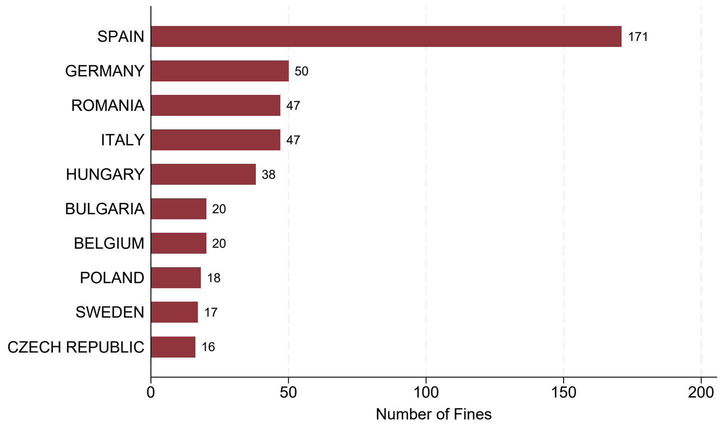

Figure 2.5: Leading 10 EEA Countries by Number of GDPR Fines Levied (2018–2020)

This variation in enforcement is not merely procedural—it may have material implications for credit markets. In the context of financial regulation, the credibility of enforcement has long been seen as critical to institutional effectiveness. For example, Bhattacharya and Daouk (2002) show that financial markets only respond to insider trading laws once they are credibly enforced. Leuz and Wysocki (2016) and Almeida Teixeira et al. (2019) similarly argue that regulatory uncertainty declines—and investor or firm behavior adjusts—only when laws are meaningfully implemented.

4.3 Empirical Strategy

This study investigates whether the introduction of a stringent data protection regime, namely the GDPR, affects access to alternative credit. Among potential identification strategies—Synthetic Control (SC), Synthetic Difference-in-Differences (SDiD), and Difference-in-Differences (DiD)—the DiD approach is selected as the benchmark due to its flexibility, tractability, and established use in evaluating block policy interventions. DiD is particularly well suited to this context, as it estimates average treatment effects by comparing outcomes over time between treated and control groups, while accommodating key design features such as policy anticipation, enforcement heterogeneity, and interactions with market structure. The canonical two-way fixed effects DiD specification is adopted for its transparency, interpretability, and ability to isolate the average treatment effect on the treated. Supporting diagnoses, including event-time plots and placebo regressions, reinforce the plausibility of the parallel trends assumption during the pre-treatment period.

To ensure robustness, the study also applies the SDiD estimator developed by Arkhangelsky et al. (2021). SDiD constructs outcome-weighted comparisons that balance pre-treatment trends and covariates across treated and control units, and it competes with canonical estimators in settings with variable treatment timing and baseline heterogeneity. While SDiD retains fixed effects and enhances pre-treatment comparability, it does not readily accommodate multiple interactions with institutional variables or moderators, which are central to this study's framework. Accordingly, SDiD serves as a robustness check to validate the baseline DiD estimates.

Although the Synthetic Control Method (SCM), introduced by Abadie et al. (2010), is well suited for evaluating interventions affecting a single unit or a few treated units with staggered adoption, it is not applicable to the context analyzed in this study. The GDPR was implemented uniformly across all European Economic Area (EEA) countries in 2018, creating a block treatment structure that lies outside the methodological scope of SCM.

To implement the empirical strategy, this study examines the GDPR, which came into effect in May 2018. All European Union member states, along with Iceland, Liechtenstein, and Norway in the European Economic Area (EEA), adopted the regulation and constitute the treatment group. The potential control group includes countries that had not implemented GDPR-like regulations during the study period, such as Canada, the United States, China, India, Australia, Japan, Indonesia, Malaysia, Albania, Russia, Bosnia and Herzegovina, Belarus, Moldova, Serbia, Turkey, and Ukraine. While the United States introduced the California Consumer Privacy Act (CCPA) at the state level in 2020, it lacks an equivalent national regulation. Control countries are selected based on both data availability and the absence of GDPR-like strong comparable data protection laws. Figure 2.6 presents the countries included in the study, distinguishing between treated and control groups based on GDPR adoption status.

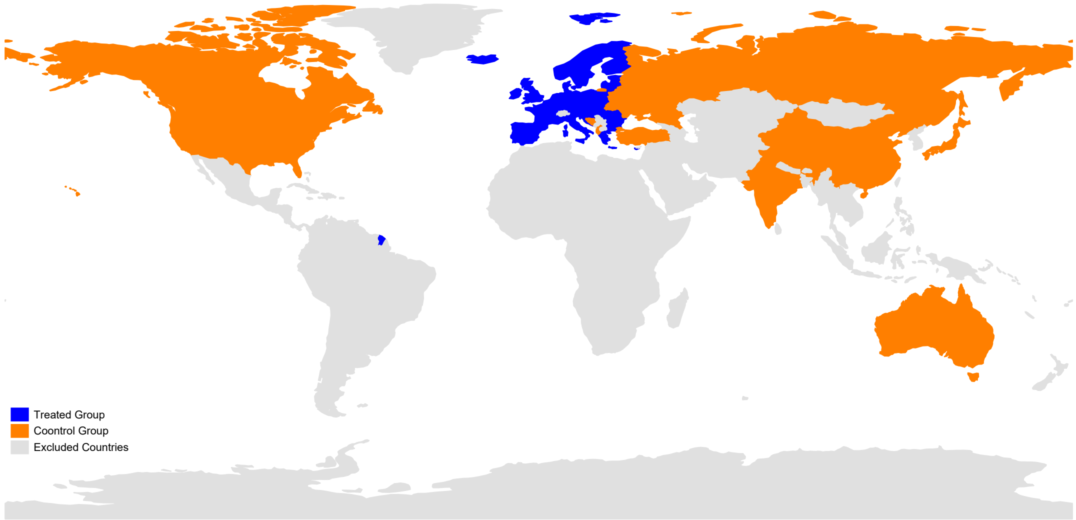

Figure 2.6: GDPR Treatment and Control Country Groups ·

· Countries in the EEA subject to GDPR enforcement from 2018 are shown in blue. Control countries without GDPR-like regulation during the study period are shown in orange. Countries not included in the sample appear in light gray. Although geographically located in Latin America, French Guiana is shaded as "GDPR Treated" because it is an overseas department of France and therefore subject to European Union jurisdiction.

Identifying the causal effect of data regulation on FinTech and BigTech credit provision presents several empirical challenges. A simple before-and-after comparison within EEA countries risks confounding the effect of GDPR with time trends or macroeconomic shocks. Similarly, cross-sectional comparisons between EEA and non-EEA countries may suffer from bias due to pre-existing differences in baseline credit penetration and regulatory environments. The DiD framework addresses these limitations by implementing a double-differencing strategy—comparing the change in outcomes before and after the GDPR in the treatment group to the corresponding change in the control group. This approach helps isolate the counterfactual trajectory and identify the causal effect attributable to the GDPR intervention.

A formal derivation of the DiD estimator, including the underlying identification assumptions and functional form of the treatment effect, is provided in Appendix E. Appendix E outlines the the theoretical framework by modeling the counterfactual evolution of alternative credit in the absence of regulation and expressing the average treatment effect as a double-differenced estimator.

Building on this framework, the empirical specification introduces a vector of time-varying covariates, together with country and year fixed effects, to account for residual sources of heterogeneity. The resulting baseline regression model is:

$$\text{AC}_{it} = \beta_0 + \beta_1 \text{Post}_t + \beta_2 \text{Treated}_i + \delta(\text{Post}_t \times \text{Treated}_i) + X_{it}'\psi + \alpha_t + \gamma_i + \epsilon_{it} \quad (2.1)$$

where, AC_{it} denotes the volume of alternative credit (FinTech, BigTech, or both) in country i at time t. The variable Post_t is a dummy equal to 1 for years $t \geq 2018$, and 0 otherwise. Treated_i equals 1 for EEA countries subject to GDPR and 0 for control countries. The coefficient of the interaction $\text{Post}_t \times \text{Treated}_i$ δ, captures the causal effect of GDPR. α_t and γ_i denote time and country fixed effects, respectively, and ϵ_{it} is the idiosyncratic error term. The control vector X_{it} includes GDP per capita, its square, the Lerner Index, regulatory stringency, trade openness, population growth, bank branches per capita, broadband subscriptions, governance indicators, and consumer trust in technology companies.

One potential concern in this identification strategy is the possibility of anticipation effects. Although the GDPR was enacted in May 2018, it was formally announced in 2016, providing firms ample time to adapt—either by relocating to more permissive jurisdictions (forum shopping) or modifying their legal basis for data processing (e.g., shifting from consent to contractual necessity), as noted by Dorfleitner et al. (2023) and Martin et al. (2019). To capture such preemptive behavior, the analysis incorporates a binary variable for the anticipation period (2016–2017) and its interaction with the treatment indicator. This approach follows prior empirical strategies in policy evaluation studies (Alpert, 2016; Blundell et al., 2011; Callaway & Sant'Anna, 2021).

The anticipation-adjusted specification is:

$$\begin{aligned} \text{AC}_{it} = \beta_0 &+ \beta_1 \text{Treated}_i + \phi_1 \text{Anticipation}_t + \phi_2(\text{Anticipation}_t \times \text{Treated}_i) \\ &+ X_{it}'\psi + \alpha_t + \gamma_i + \epsilon_{it} \end{aligned} \quad (2.2)$$

To jointly estimate both anticipation and post-treatment effects, the extended model is:

$$\begin{aligned} \text{AC}_{it} = \beta_0 &+ \beta_1 \text{Treated}_i + \beta_2 \text{Post}_t + \delta(\text{Post}_t \times \text{Treated}_i) \\ &+ \phi_1 \text{Anticipation}_t + \phi_2(\text{Anticipation}_t \times \text{Treated}_i) + X_{it}'\psi + \alpha_t + \gamma_i + \epsilon_{it} \end{aligned} \quad (2.3)$$

where, Anticipation_t is a dummy equal to 1 for the anticipation window (2016–2017), and 0 otherwise. The term $\text{Anticipation}_t \times \text{Treated}_i$ estimates any preemptive behavioral adjustments in response to the forthcoming regulation. A statistically significant ϕ_2 suggests an anticipation effect, indicating firms responded before formal enforcement. An insignificant ϕ_2 would suggest limited pre-regulatory adjustment. All other variables and fixed effects are defined as in Equation 2.1.

As a robustness check, the analysis incorporates the Synthetic Difference-in-Differences (SDiD) estimator developed by Arkhangelsky et al. (2021). This method combines features of traditional DiD and the Synthetic Control approach to relax the parallel trends assumption and improve causal identification. By re-weighting pre-treatment observations, SDiD constructs a counterfactual trajectory more closely aligned with the treated group while preserving the fixed-effects structure of the baseline model. A formal exposition of the estimator, including identification assumptions and implementation details, is provided in Appendix F.

To probe whether the observed GDPR effects reflect an overall expansion in credit markets or a structural shift in credit allocation, the analysis extends the baseline specification in Equation 2.1 by estimating Difference-in-Differences models using alternative outcome variables. Specifically, two dimensions are explored: the total volume of credit—including bank, FinTech, and BigTech lending—and the share of alternative credit relative to total lending. The former captures the broader macro-financial consequences of GDPR, while the latter isolates compositional changes in credit supply. By contrasting these outcomes, the analysis distinguishes whether the regulation stimulates general credit growth or induces a reallocation toward nonbank digital intermediaries. This distinction offers important insights into the mechanisms through which data protection regulation interacts with financial intermediation.

The first extension uses total lending—defined as the sum of bank, FinTech, and BigTech credit—as the dependent variable. This captures the overall impact of GDPR on aggregate credit supply. Comparing these results to the baseline estimates from Equation 2.1, where alternative credit volumes serve as outcomes, helps assess whether digital lenders disproportionately benefit from data privacy regulation. The second extension focuses on the ratio of alternative credit to total lending, which isolates compositional shifts in credit allocation. A statistically significant and positive treatment effect in this specification would indicate that GDPR not only influences total credit volume but also reshapes the structure of credit markets in favor of digital finance.

To account for cross-country variation in the effectiveness of GDPR implementation, the analysis augment Equation 2.1 by interacting the treatment indicator with an index capturing the intensity of enforcement. This extension tests whether the regulation's impact on alternative credit is conditional on enforcement mechanisms and legal credibility. A statistically significant and positive interaction term would suggest that stronger enforcement amplifies the regulatory effect, reinforcing the view that formal adoption alone is insufficient to reshape credit allocation. Instead, meaningful policy outcomes depend on the credibility of enforcement and the broader institutional environment in which the regulation is applied.

As an additional robustness check, the analysis employs entropy balancing to improve covariate balance between treated and control groups prior to GDPR implementation. While Propensity Score Matching is widely used, it relies on nearest-neighbor matching and often discards unmatched observations. In contrast, entropy balancing reweights control observations so that selected moments of the covariates—typically the mean, variance, and skewness—exactly match those of the treated group (Hainmueller, 2012). This method retains the full sample, imposes fewer assumptions about functional form, and enhances the credibility of causal inference. Blind et al. (2024) similarly applies entropy balancing in their analysis of the effect of GDPR on the German market firms' product innovations.

5 Results and Discussion

A critical identifying assumption in Difference-in-Differences (DiD) estimation is the presence of parallel trends between treatment and control groups prior to the intervention. Table B5 reports the results from estimating Equation 2.1 using only pre-treatment data. The coefficient on the variable *Treated* is negative and statistically significant across all credit types, indicating that, before GDPR implementation, average FinTech, BigTech, and alternative credit volumes were significantly lower in treated countries compared to the control group.

In contrast, the coefficients for *post* are positive and statistically significant for all credit categories, suggesting an upward trend in credit volumes in both groups, independent of the regulation. The interaction term *post* × *treated*—which captures differential trends between treated and control groups before the intervention—is statistically insignificant across all specifications. This confirms that no pre-treatment divergence existed in credit growth between the two groups, thereby validating the parallel trends assumption. Figures B.2, B.3, and B.4 further corroborate this finding by illustrating visually parallel trajectories in alternative, FinTech, and BigTech credit volumes prior to the GDPR intervention. The placebo results in Table B6 provide additional confirmation that the parallel trends assumption holds.

Table 2.1 presents the main DiD estimation results, which include controls for country income group, geographic region, year-fixed effects, and other covariates as specified in Equation 2.1. Column (1) uses alternative credit as the dependent variable; Columns (2) and (3) separately examine FinTech and BigTech credit. The coefficient on *Treated* remains negative and statistically significant for both FinTech and alternative credit, consistent with lower baseline credit levels in the treated group. The coefficient on *post* is positive and statistically significant for both FinTech and alternative credit, indicating a general increase in digital credit volumes over time, irrespective of treatment. For BigTech credit, the coefficient is positive but not statistically significant, suggesting that the overall temporal trend driving increases in digital credit is not primarily attributable to BigTech lenders.

Notably, this pattern is also visible in the heterogeneity analysis presented in Table 2.2. The coefficients on the *post* and *treated* indicators are consistently signed across all five interaction specifications. The GDPR period is associated with a positive, statistically significant shift in the overall time trend of digital credit, reinforcing the view that GDPR coincided with a broader upward trajectory in technology-based lending across both treated and control countries.

The main variable of interest, *post* $\times$ *treated*, is positive and statistically significant across all three specifications. The estimates indicate that the GDPR increased alternative credit volumes in treated countries by approximately 1.08 to 1.75 percentage points. In the absence of GDPR implementation, credit volumes in these countries would have been correspondingly lower, indicating that GDPR is associated with a measurable increase in digital credit within the treated countries post-2018. The effect is most pronounced for alternative credit and FinTech credit. This result is consistent with the findings of Doerr, Gambacorta, et al. (2023), who show that data privacy regulations can particularly foster the development of alternative credit markets, conditional on income group controls and unobserved time-varying confounders being limited.

The mechanism through which the GDPR influences alternative credit expansion appears to operate through a combination of structural conditions and institutional interactions, as outlined in Table 2.2. A key channel lies in the regulation's emphasis on transparency, user consent, and data portability, which may contribute to greater consumer confidence in digital financial services. While the standalone effect of the trust index is weak or only marginally significant in the baseline specifications for FinTech and alternative credit—and statistically insignificant for BigTech—the interaction term *GDPR* $\times$ *Trust* is both positive and statistically significant in the alternative credit model. This suggests that the effectiveness of the GDPR in promoting alternative credit growth is likely conditional on the prevailing level of institutional trust. In countries where trust in digital systems and financial intermediaries is already high, enhanced privacy protections may reduce perceived risks related to data sharing, thereby fostering broader engagement with non-traditional credit providers. This interpretation aligns with a growing body of literature emphasizing the role of institutional trust in shaping the adoption and diffusion of privacy-compliant financial technologies (Armantier et al., 2021; Boissay et al., 2021; Doerr, Gambacorta, et al., 2023).

Table 2.1: Baseline DiD Estimation with Four Countries Control Group

	(1) Alt.Credit	(2) FinTech Credit	(3) BigTech Credit
Treated	-1.635***	-1.297**	-9.261***
	(0.490)	(0.642)	(0.830)
Post	5.542*	4.564**	0.088
	(2.976)	(2.294)	(0.338)
Post*Treated	1.748***	1.310***	1.076**
	(0.596)	(0.440)	(0.487)
Bank regulatory index	-7.626*	-5.273	-0.094
	(4.274)	(3.211)	(0.462)
LernerIndex	0.705	0.371	0.420
	(0.568)	(0.406)	(0.371)
Mobile subscriptions	0.803***	0.776***	2.026*
	(0.207)	(0.179)	(1.127)
Bank Branches	0.311	0.153	-2.847
	(0.420)	(0.392)	(2.061)
Trust index	0.802*	0.591*	0.790
	(0.460)	(0.387)	(0.882)
GDP per capita	-0.228	-0.116	8.088***
	(1.234)	(1.098)	(3.501)
Inflation	0.418***	0.316***	-0.038
	(0.098)	(0.052)	(0.076)
Constant	-23.440*	-22.986*	-45.570***
	(13.770)	(11.970)	(54.505)
Year FE	Yes	Yes	NO
Region FE	Yes	Yes	Yes
Income level FE	Yes	Yes	Yes
Adj.R-squared	0.514	0.615	0.965
N	185	185	20

All the regressors are lagged and expressed in natural logarithmic form, except for inflation and the dummy variables. This table reports results for Equation 2.1. The dependent variables are the log of Alternative Credit (column 1), FinTech Credit (column 2), and BigTech Credit (column 3), each winsorized at the 1% and 99% levels. The dummy variable *treated* equals one if the country belongs to the treatment group (EEA countries), and zero for countries in the control group (United States, Canada, Australia, and Japan). The dummy variable *post* equals one for all years following the enactment of the GDPR in 2018. GDP per capita growth and economic openness were included in the estimation but are not reported. The sample is divided into six geographic regions: Africa, Asia Pacific, Europe, Latin America, the Middle East, and North America. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Moreover, the interaction term *GDPR × Mobile Subscriptions* is positive and statistically significant, indicating that the regulation's positive effect on alternative credit is stronger in countries with high mobile penetration. This finding supports the interpretation that technology infrastructure enables GDPR-compliant lenders to scale more efficiently. Mobile-based platforms provide critical functionality for secure consent management, user authentication, and app-based compliance, all of which become vital under tighter data regulation consistent with the findings of Cornelli et al. (2020).

The positive and statistically significant interaction between GDPR and the Lerner Index supports the hypothesis that regulatory impacts are shaped by underlying market structure. In markets characterized by high bank market power, the GDPR facilitates a greater shift toward alternative credit. This finding is consistent with a substitution mechanism, where borrowers excluded or underserved by traditional banks respond more readily to enhanced privacy safeguards offered by FinTech and BigTech platforms. Moreover, it suggests that the GDPR may partially level the playing field in otherwise concentrated banking systems, enabling regulatory arbitrage by technologically adaptive lenders.

The analysis further reveals that the GDPR is more effective in jurisdictions with higher-quality governance. The interaction term *GDPR* $\times$ *Governance Indicator* is positive and significant, consistent with the idea that regulatory clarity and institutional strength mitigate compliance frictions and enhance the capacity of alternative lenders to adjust. A similar pattern emerges for market concentration: the negative interaction between GDPR and concentration suggests that more competitive lending environments generate stronger regulatory effects. Together, these findings point to a multidimensional set of conditions under which privacy regulation facilitates alternative credit expansion.

Market concentration also emerges as a factor shaping the regulatory impact of the GDPR on alternative credit. The interaction term *GDPR* $\times$ *Concentration* is negative and statistically significant in Table 2.2. This finding suggests that the effectiveness of the GDPR in promoting alternative credit is weaker in highly concentrated banking markets. One plausible explanation is that incumbent financial institutions exert significant control over credit allocation, data infrastructure, and regulatory compliance practices in such environments. These dominant players may limit the entry or scaling of platform-based lending by restricting market access or shaping regulatory implementation to favor incumbents. In contrast, less concentrated markets with greater competitive pressure provide digital lenders more space to compete through GDPR compliance, transparency, and user-centric data governance. This interpretation aligns with studies highlighting how market concentration influences the diffusion of financial innovation and the growth of new entrants (Gal & Aviv, 2020; Geradin et al., 2021; Johnson, 2022).

Table 2.2: Mechanisms and Heterogeneity in the GDPR's Impact on Alternative Credit

	(1)	(2)	(3)	(4)	(5)
Treated	-1.903***	-4.826***	-4.822***	-4.120***	-2.493***
	(0.601)	(1.480)	(1.685)	(1.007)	(0.677)
Post	1.990***	1.790***	3.285***	2.657***	2.187***
	(0.301)	(0.411)	(0.395)	(0.314)	(0.561)
Post*Treated	9.694**	1.349**	2.713***	8.244***	4.212***
	(4.189)	(0.620)	(0.751)	(2.328)	(1.088)
Mobile subscriptions	1.783***				
	(0.413)				
Lerner Index		0.886*			
		(0.519)			
Governance indicator			0.316		
			(1.085)		
Concentration				-0.030**	
				(0.021)	
Trust Index					0.935**
					(0.475)
GDPR × Mobile subscriptions	0.493**				
	(0.249)				
GDPR × Lerner Index		0.301*			
		(0.699)			
GDPR × governance indicator			1.403**		
			(0.677)		
GDPR × Concentration				-0.033**	
				(0.016)	
GDPR × Trust index					1.703***
					(0.658)
Constant	-39.290***	2.932*	1.329	4.225**	-12.242***
	(7.067)	(1.743)	(2.217)	(1.980)	(1.210)
Year FE	YES	YES	YES	YES	YES
IncomeGroup FE	YES	YES	YES	YES	YES
Adj.R-squared	0.558	0.555	0.571	0.677	0.564
N	233	228	269	237	247

This table presents results from estimating Equation 2.1, augmented with interaction terms to explore potential mechanisms through which the GDPR affects alternative credit markets. The dependent variable is the natural logarithm of alternative credit, winsorized at the 1% and 99% levels to mitigate the influence of outliers. The variable *treated* equals one for countries in the treatment group (EEA members) and zero for control countries (United States, Canada, Australia, and Japan). The variable *post* equals one for all years following the enforcement of the GDPR in 2018. Interaction terms capture how the GDPR's effect varies by mobile infrastructure, market power, institutional trust, governance quality, and market concentration. All models include fixed effects for year, income group, and region. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Beyond the moderating mechanisms explored above, examining the role of other covariates offers further insight into the structure of the alternative credit market. Results from both Table 2.1 and Table 2.2 highlight the critical role of digital infrastructure. Mobile subscriptions are consistently associated with higher levels of alternative credit, underscoring the enabling role of mobile technology in extending financial access—particularly in underserved regions. This pattern reinforces the broader interpretation that digital capacity remains a foundational precondition for scalable, technology-based lending models. Haddad and Hornuf (2019) found similar results.

Stringent banking regulations negatively but weakly affect alternative credit. Stringent regulations often restrict the types of financial services non-bank entities can offer or influence their operations in financial markets. Although stricter banking rules, such as tighter licensing regimes or constraints on partnerships, can inhibit innovation and limit the use of data-driven credit models, many alternative credit providers operate outside the core regulatory perimeter or specialize in underbanked segments that are less directly impacted. This result is broadly consistent with prior findings by Claessens et al. (2018), Cornelli et al. (2023), Frost et al. (2019), and Navaretti et al. (2018).

Inflation positively and significantly affects both alternative and FinTech credit across all model specifications. This result is robust to various estimation settings, including (i) using the United States, Canada, Japan, and Australia as the control group (Table 2.1); (ii) excluding the United States (Table B8); (iii) accounting for anticipation effects (Table 2.3); (iv) including both anticipation and post-treatment dummies (Table B7); and (v) expanding the control group to 13 countries (Table 2.4). In contrast, inflation tends to have a negative, though inconsistent, effect on BigTech credit. This divergence likely reflects differences in target markets and business models. BigTech lenders often serve higher-income consumers and established businesses, segments more likely to reduce borrowing as inflation raises interest rates and financing costs. For example, Lanxon and Burke (2022) reports that BigTech profits declined by approximately 10% during the 2021–2022 inflation surge, as advertisers cut spending and consumer demand weakened, particularly in price-sensitive sectors such as streaming services. By contrast, FinTech firms primarily serve underbanked groups such as small businesses and lower-income households, which are more likely to experience liquidity constraints during inflationary periods. These borrowers tend to rely on fast, flexible, and short-term credit that FinTech lenders offer. Moreover, FinTech firms can remain profitable by offering smaller loans at higher interest rates, making them relatively resilient during inflation shocks. This interpretation aligns with the findings of Cornelli et al. (2020) and Jagtiani and Lemieux (2018), who show that FinTechs often gain market share in economically challenging environments. Moreover, countries witness an increase in access to FinTech credit when the economy is well-developed, consistent with the findings by Cornelli et al. (2023) and Haddad and Hornuf (2019)

Alternative Specifications and Robustness Checks

This section implements a series of robustness checks to verify the stability of the main results. These include accounting for potential anticipation effects, modifying the composition of the control group through expansion and reduction, re-estimating the model using alternative dependent variables such as total credit and the ratio of alternative to total credit, applying the Synthetic Difference-in-Differences (SDiD) method, and incorporating entropy balancing prior to DiD estimation.

The first robustness check addresses the potential anticipatory effects surrounding the announcement of the GDPR. Although the regulation came into force in May 2018, it was officially announced in 2016, providing firms with substantial lead time to adapt. During this interim period, companies may have proactively adjusted their business models—such as relocating operations, revising data governance frameworks, or shifting the legal basis for data processing from user consent to contract fulfillment—as documented by Dorfleitner et al. (2023) and Martin et al. (2019). To test for such pre-treatment adjustments, I estimate Equation 2.2, following the framework of Alpert (2016), Blundell et al. (2011), and Callaway and Sant'Anna (2021). In this specification, a significant coefficient on the interaction term $\textit{Treated} \times \textit{Anticipation}$ would suggest an anticipatory response among treated countries. Conversely, an insignificant coefficient would indicate that the alternative credit market in GDPR-implementing countries did not react in a statistically meaningful way to the regulation's announcement, suggesting the absence of anticipatory effects.

Figure B.1 displays Google search trends related to the General Data Protection Regulation (GDPR) between 2016 and 2020. The data indicates minimal public interest in the GDPR during its announcement year in 2016, with search volume remaining low until early 2018. Interest increased sharply in the months leading up to the regulation's enforcement in May 2018, peaking at the time of implementation in both the European Economic

Area (orange) and the rest of the world (green). This pattern suggests that widespread awareness and concern regarding the GDPR emerged right before its enforcement. Consistent with this trend, Jia et al. (2018) documents that firms began making substantial adjustments in early 2018, as the anticipated costs and operational implications of compliance became more apparent. This was particularly evident in the month preceding enforcement, when major digital platforms—including Google, Facebook, Amazon, and Apple—began adopting stricter data sharing, portability, and liability policies.

While many technology firms and digital platforms may have begun preparing for the GDPR prior to its 2018 enforcement, firms operating in the alternative credit market may not have perceived an immediate need for anticipatory adjustments. If the GDPR announcement did not signal an urgent regulatory risk or strategic opportunity for this sector, firms may have deferred compliance efforts until enforcement became imminent. This delayed response may reflect the relatively low salience of the GDPR within the alternative credit space, as suggested by Figure B.1, which shows limited public attention to the regulation in its early stages. Moreover, the GDPR may not have appeared sufficiently threatening or transformative to prompt early restructuring in credit operations. Supporting this view, Johnson (2022) note that privacy regulators lacked enforcement experience and precedent during the initial rollout, reducing firms' perceived risk of non-compliance. Similarly, a survey by TrustArc (2018) found that most firms were still in the process of implementing compliance measures by the enforcement deadline, suggesting that full alignment with the regulation was widely delayed across sectors.

The results in Table 2.3 support the argument that the GDPR announcement did not influence firms' credit extension decisions. The coefficient of *Anticipation* is positive and statistically significant for both alternative and FinTech credit, indicating a common shift across treated and control groups during the announcement period. However, the main variable of interest, *Treated* $\times$ *Anticipation*, is statistically insignificant, suggesting that firms in the treated group did not begin adjusting their behavior in response to the regulation's announcement. As an additional robustness check, I estimate Equation 2.3, which includes both the *Post* and *Anticipation* dummies to separately capture post-enforcement effects and any anticipatory adjustments. The corresponding results, presented in Table B7, again show that *Treated* $\times$ *Anticipation* remains insignificant across all credit categories. This further reinforces the conclusion that firms in the alternative credit sector did not respond meaningfully to the GDPR prior to its implementation.

Table 2.3: DiD Estimation Accounting for Anticipation Effects (Four-Country Control Group)

	(1) Alt.Credit	(2) FinTech Credit	(3) BigTech Credit
Treated	-2.327***	-1.561	-11.857***
	(0.878)	(1.050)	(3.102)
Anticipation	7.162**	7.680**	-0.443
	(3.213)	(3.248)	(0.370)
Anticipation × Treated	-0.022	-0.320	-0.941
	(0.541)	(0.581)	(0.592)
Bank regulatory index	-7.889*	-7.788*	-0.697
	(4.395)	(4.499)	(1.037)
Lerner Index	0.513	0.692	0.252
	(0.546)	(0.492)	(0.457)
Mobile subscriptions	1.130***	1.346***	-0.351
	(0.349)	(0.354)	(3.852)
Bank Branches	0.006	0.060	1.844
	(0.587)	(0.573)	(3.893)
Trust index	1.094**	2.627*	2.384
	(0.428)	(1.531)	(3.355)
GDP per capita growth	0.103	0.098	-0.030
	(0.191)	(0.173)	(0.398)
Inflation	0.389***	0.388***	-0.011
	(0.102)	(0.093)	(0.162)
Openness	1.744	1.333	-5.898
	(1.130)	(1.110)	(4.722)
Constant	-40.749***	-49.370***	33.388
	(13.608)	(13.207)	(32.104)
Year FE	Yes	Yes	NO
Region FE	Yes	Yes	Yes
Adj.R-squared	0.505	0.576	0.966
N	185	185	20

All regressors are lagged and expressed in natural logarithmic form, except for inflation and the dummy variables. This table reports results from estimating Equation 2.2. The dependent variables are the log of alternative credit (Column 1), FinTech credit (Column 2), and BigTech credit (Column 3), each winsorized at the 1% and 99% levels. The dummy variable *Treat* equals one for countries in the treated group (EEA) and zero for those in the control group (United States, Canada, Australia, and Japan). The dummy variable *Anticipation* equals one for the period between the GDPR announcement and enforcement (2016–2017). Governance indicators and population growth rates were included in the regressions, but are omitted from the table for brevity.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As a further robustness check, I re-estimate Equation 2.1 after excluding the United States from the control group used in Table 2.1. Although the US lacks comprehensive national privacy regulation, the state of California enacted the California Consumer Privacy Act (CCPA), which came into effect in 2020. The CCPA grants users increased control over their personal data and restricts certain types of data use, potentially affecting credit models built on data aggregation. To avoid confounding effects from this state-level policy, I exclude the United States from the sample and re-estimate the model using the remaining country control group. Figures B.5, B.6, and B.7 show that alternative credit, FinTech credit, and BigTech credit, respectively, exhibit similar trends between the treated and control group before the GDPR intervention, satisfying the parallel trend assumption in this restricted sample.

Table B8 presents the results of the robustness check in which the United States is excluded from the control group. Prior to the GDPR intervention, credit volumes across all categories—alternative, FinTech, and BigTech—were lower in the treated group relative to the control group. Following the intervention, both alternative and FinTech credit volumes increased in the control group, as indicated by the positive and significant *Post* coefficients. In contrast, the *Post* coefficient for BigTech credit remains statistically insignificant, suggesting no substantial shift in BigTech lending over the period. Consistent with the baseline results reported in Table 2.1, the DiD interaction term δ remains positive and statistically significant across all credit types, reaffirming the conclusion that the GDPR had a positive causal impact on alternative credit extension.

As a further robustness check, I expand the control group to include thirteen countries[13] that, during the study period, had not adopted GDPR-equivalent privacy regulations. This broader comparison group allows for a more generalizable test of the treatment effect while still maintaining regulatory comparability. To avoid skew from extreme market outliers, I exclude the United States and China from this estimation. Both countries have disproportionately large credit markets, and the United States introduced state-level legislation, the CCPA, in 2020. Their exclusion ensures that the remaining countries are more representative of the typical non-GDPR jurisdiction.

Figures B.8, B.9, and B.10 confirm that the treated and control groups follow parallel pre-trends in alternative, FinTech, and BigTech credit, respectively. Table B9 further supports this by showing that the $Post \times Treated$ interaction term is statistically insignificant in the pre-intervention period. Estimation results from Equation 2.1, reported in Table 2.4, show that the GDPR had a positive and statistically significant effect on FinTech and alternative credit, while the effect on BigTech credit remains insignificant, consistent with

[13] Albania, Australia, Belarus, Bosnia and Herzegovina, Canada, India, Japan, Kosovo, Moldova, Russia, Serbia, Turkey, and Ukraine

baseline results.

Table 2.4: DiD estimation with 13 Countries Control Group

	(1) Alt.Credit	(2) FinTech Credit	(3) BigTech Credit
Treated	-0.984	-0.730	-0.078
	(1.147)	(0.957)	(0.078)
Post	3.250	4.043*	0.183*
	(2.288)	(2.368)	(0.107)
Post*Treated	1.045**	1.028***	-0.172
	(0.498)	(0.361)	(0.105)
Bank regulatory index	-2.532	-3.756	0.004
	(3.070)	(3.156)	(0.010)
Mobile subscriptions	1.080***	1.158***	0.225*
	(0.400)	(0.362)	(0.118)
Bank Branches	0.205	0.053	0.054**
	(0.381)	(0.360)	(0.027)
Trust index	2.347*	1.270	-0.057
	(1.418)	(0.871)	(0.095)
GDPpc growth	-0.064	-0.097	-0.005
	(0.158)	(0.124)	(0.008)
Popln Growth	-0.661	-0.457	-0.252**
	(0.416)	(0.364)	(0.123)
Inflation	0.148*	0.157**	-0.013**
	(0.080)	(0.069)	(0.006)
Constant	-29.803***	-42.124***	1.999
	(11.142)	(14.301)	(1.684)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Adj.R-squared	0.659	0.667	0.163
N	181	179	173

All the regressors are lagged and expressed in natural logarithmic form except for inflation and the dummies. This table reports results for Equation 2.1. The dependent variables are the log of alternative credit(column 1), the log of FinTech credit(column 2), and BigTech credit volume(column 3), and have been winsorized at the 1% and 99% level. *Treat* takes on a value of 1 for countries in the treated group (EEA countries) and 0 for countries in the control group. GDP per capita, Lerner index, and economic openness were also estimated but not reported.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As an additional robustness check, I apply the Synthetic Difference-in-Differences (SDiD) method using the full sample of fifteen control countries, including the United States and China. The SDiD approach strengthens causal inference by constructing weighted averages of untreated units that closely resemble the treated group during the pre-treatment period (Arkhangelsky et al., 2021), while also relaxing the assumption of uniform trends across units. The estimation uses the same outcome variables as in previous specifications. Figures B.11, B.12, and B.13 display the estimated trends for FinTech, alternative credit, and BigTech credit, respectively. The interaction term *Post* × *Treated* captures the average treatment effect of the GDPR. Results reported in Table 2.5 corroborate the direction and statistical significance of the DiD estimates: the GDPR led to a significant increase in FinTech and alternative credit volumes, while the effect on BigTech credit remains statistically insignificant. The estimates remain robust to the inclusion of the endogenous lag of the dependent variable. The positive and statistically significant coefficients for FinTech and alternative credit persist across both specifications, whereas the estimates for BigTech credit continue to display large standard errors and remain statistically insignificant.

Table 2.5: Synthetic Difference in Difference Estimation

	(1) Alternative Credit	(2) FinTech Credit	(3) BigTech Credit	(4) BigTech Credit
Post × *Treated*	0.004**	0.867***	18.336	-5.119
	(0.002)	(0.327)	(54.950)	(42.732)
Observations	360	216	240	208
Considering Endogenous Lag of Dependent Variables				
Post × *Treated*	0.004**	0.647**	15.297	5.993
	(0.002)	(0.481)	(35.070)	(5.347)
Observations	315	171	210	182

All regressors are lagged and expressed in natural logarithmic form, except for inflation and dummy variables. This table reports results from Equation 2.1 using SDiD estimation. The dependent variables are: log of alternative credit (Column 1), log of FinTech credit (Column 2), and BigTech credit volume in millions of USD (Columns 3 and 4), all winsorized at the 1% and 99% levels. Column 4 uses BigTech credit with a restricted control group (U.S., Japan, Canada, and Australia). The interaction term *Post* × *Treated* equals one for treated countries in years $\geq$ 2018. Controls include GDP per capita, regulatory index, inflation, population, income group dummies, and openness. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Building on the previous robustness checks that examined baseline differences and treatment effects following the GDPR's introduction, this study also investigates whether the regulation's effectiveness varied systematically with the intensity of its enforcement. This allows for a more refined understanding of how enforcement credibility, measured by total fine volumes, conditions the response of digital credit markets to regulatory reform.

Table 2.6 presents the results. Column (1) examines the relationship between GDPR enforcement and total alternative credit, while Column (2) isolates the effect on FinTech credit specifically. Column (3) focuses on high-enforcement countries—those in the top quartile of cumulative fines—to assess whether enforcement intensity amplifies the policy's impact. Column (4) further restricts the sample to GDPR-affected countries and treats enforcement as a continuous measure of treatment intensity, allowing for a finer-grained assessment of how varying levels of enforcement shape post-GDPR credit outcomes.

The results indicate that enforcement plays a central role in shaping the relationship between the GDPR and alternative credit growth. In both alternative and FinTech credit markets, jurisdictions with stronger enforcement experienced significantly greater post-GDPR credit expansion. Rather than inhibiting growth by increasing compliance costs, credible enforcement may have reinforced institutional trust and signaled regulatory seriousness, encouraging consumer participation and credit expansion. In high-enforcement jurisdictions, this effect becomes even more pronounced, suggesting that enforcement serves not only as a deterrent but also as a confidence signal that strengthens the perceived reliability of digital finance and enhances perceptions of oversight quality and institutional capacity.

Table 2.6: Enforcement Intensity and GDPR Effects

	(1) Alt. Credit	(2) FinTech Credit	(3) Top Quartile	(4) Marginal Effect
GDPR × Enforcement	0.013**	0.013**	0.502**	0.437*
	(0.006)	(0.006)	(0.227)	(0.237)
Bank Regulatory Index	0.000	0.000	2.888***	3.124***
	(.)	(.)	(0.446)	(0.537)
Lerner Index	0.694	0.681	0.749	0.759
	(1.255)	(1.263)	(0.626)	(0.734)
GDP per Capita Growth	-0.429	-0.483	0.515**	0.487*
	(0.381)	(0.384)	(0.228)	(0.251)
Constant	-17.149*	-21.902*	0.590	-0.091
	(276.970)	(278.446)	(0.998)	(1.082)
Year FE	Yes	Yes	Yes	Yes
Income Group FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.422	0.445	0.469	0.471
N	50	50	193	167

The table reports robustness results on GDPR enforcement. The dependent variables are: log of alternative credit (Column 1), log of FinTech credit (Column 2), and log of alternative credit in subsamples defined by high enforcement intensity (Column 3) and continuous enforcement exposure (Column 4), respectively. The interaction term captures post-GDPR treatment moderated by enforcement intensity. All specifications include year and income group fixed effects. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Column 4 further supports this view by demonstrating that, within GDPR-affected countries, enforcement intensity is positively correlated with credit growth, even when control countries are excluded. In this setting, fine volumes operate as a modifier of treatment strength. More stringent enforcement appears to reinforce regulatory clarity and digital trust—factors essential for the development of data-intensive financial markets. This highlights the potential of enforcement to catalyze responsible innovation and financial inclusion by embedding credibility within the regulatory environment.

The Difference-in-Differences estimates in Table 2.7 reveal heterogeneous effects of the GDPR on overall credit supply and its composition. The positive and statistically significant interaction term in Column (1) suggests that the GDPR was associated with an expansion of total domestic credit in treated countries. This finding counters concerns that stringent data regulation might crowd out credit due to compliance burdens, indicating that the regulation may have fostered trust in data governance and spurred credit activity.

The compositional analysis in Columns (2)–(4) shows that the GDPR also altered the structure of credit markets. The ratio of alternative credit to total credit (Column 2) rose significantly post-GDPR in treated countries, as did the FinTech-to-total credit ratio (Column 3), with both positive and statistically significant interaction terms. These findings suggest that GDPR implementation coincided with a reallocation of credit toward FinTech and alternative sources, consistent with the view that well-enforced privacy regimes can enhance consumer willingness to engage with non-traditional lenders. Notably, the effect appears strongest on the FinTech ratio, likely because FinTech firms—especially those reliant on data-driven models—stood to gain the most from enhanced data protections and clearer rules on data usage.

The effect on BigTech credit (Column 4) is also positive but weakly significant. The positive shift could reflect increased consumer trust in BigTech lenders or their ability to scale rapidly in response to regulatory clarity. The results suggest that the GDPR may have catalyzed a compositional shift toward digitally mediated credit, particularly via FinTech channels, under conditions of credible enforcement and regulatory clarity.

Table 2.7: DiD Estimation on Total Credit and Credit Ratios

	(1) Total Credit	(2) Alt/Total	(3) FinTech/Total	(4) BigTech/Total
Treated	-3.575***	-0.092***	-0.090*	-0.846**
	(1.060)	(0.025)	(0.047)	(0.405)
Post	5.702***	0.145**	0.234*	-1.228*
	(1.935)	(0.068)	(0.142)	(0.720)
Post × Treated	0.863***	0.055***	0.065***	1.214*
	(0.309)	(0.016)	(0.024)	(0.694)
Bank regulatory index	-5.851**	-0.151*	-0.338*	1.605*
	(2.622)	(0.089)	(0.203)	(0.911)
Lerner Index	0.262	0.015	0.039	1.897
	(0.406)	(0.019)	(0.028)	(1.908)
Mobile subscriptions	2.721*	0.123*	0.222**	2.875*
	(1.601)	(0.064)	(0.103)	(1.686)
Bank Branches	0.180	0.004	0.026	-0.518
	(0.387)	(0.014)	(0.023)	(0.459)
Trust index	2.688*	0.110*	0.073	0.330
	(1.492)	(0.063)	(0.075)	(1.062)
GDP per capita	2.593**	-0.011	0.051	0.227
	(1.063)	(0.037)	(0.058)	(0.235)
Advanced Economy	3.145***	0.081***	0.093***	0.694*
	(0.714)	(0.023)	(0.034)	(0.413)
Inflation	0.210***	0.010***	0.015***	0.185
	(0.064)	(0.003)	(0.004)	(0.166)
Population	-0.409	-0.093	-0.180*	0.831**
	(1.650)	(0.065)	(0.099)	(0.378)
Constant	-42.597***	-0.583*	-1.767**	-29.005**
	(8.789)	(0.322)	(0.867)	(12.406)
Year FE	Yes	Yes	Yes	Yes
IncomeGroup FE	Yes	Yes	Yes	Yes
Adj.R-squared	0.686	0.537	0.518	0.463
N	185	185	177	156

All regressors are lagged and expressed in natural logarithmic form, except for inflation and dummy variables. This table reports results from Equation 2.1 using DiD estimation. The dependent variables are: (1) Total Credit (in logs); (2) the ratio of alternative credit to total credit; (3) the ratio of FinTech credit to total credit; (4) the ratio of BigTech credit to total credit, all winsorized at the 1% and 99% levels. *Treat* takes on a value of 1 for countries in the treated group (EEA countries) and 0 for countries in the control group. GDP per capita growth and economic openness are estimated but not reported for brevity. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To improve covariate balance between treated and control units and strengthen the plausibility of the parallel trends assumption, I apply entropy balancing prior to estimating the DiD model. Entropy balancing reweights control observations so that the means (and optionally the higher moments) of selected pre-treatment covariates align with those of the treated group (Hainmueller, 2012). The resulting weights are then applied in the estimation of Equation 2.1, allowing the treatment effects to be interpreted as average treatment effects on the treated (ATT) under improved covariate comparability. Table B10 in the Appendix reports covariate balance diagnoses. The DiD results, presented in Table B11, remain consistent with the baseline estimates. The interaction term $Treated \times Post$ is positive and statistically significant at the 1% level for both alternative credit and FinTech credit, corresponding to increases of approximately 1.6 and 1.4 log points, respectively. These effects remain robust to the inclusion of institutional controls and fixed effects for year and region, reinforcing the conclusion that GDPR implementation was associated with a measurable expansion in digital credit activity in treated countries.

The effect of the GDPR on BigTech credit is inconsistent across specifications, suggesting sensitivity to model structure and sample composition. (i) When using the United States, Canada, Japan, and Australia as the control group (Table 2.1), the effect is positive and strongly significant. (ii) Excluding the United States from the control group (Table B8) yields a positive but only weakly significant coefficient. (iii) Expanding the control group to thirteen countries (Table 2.4) reverses the sign and makes the coefficient statistically insignificant. (iv) Applying the Synthetic Difference-in-Differences estimator (Table 2.5, Column 3) also produces a positive but insignificant effect. (v) When SDiD is re-estimated using the original four-country control group, the coefficient becomes negative yet remains insignificant. (vi) Using the ratio of BigTech to total credit as the dependent variable results in a weakly significant estimate. (vii) Lastly, when Difference-in-Differences is applied to entropy-balanced covariates, the result remains insignificant.

These divergent outcomes suggest that the observed positive effects in earlier specifications are likely driven by a small set of countries with mature BigTech credit markets—chiefly the United States. The inclusion of additional countries, where BigTech lending was either nascent or marginal (with the partial exception of China), appears to dilute the estimated treatment effect. This heterogeneity may reflect cross-country variation in digital infrastructure, regulatory absorption capacity, or consumer trust in platform-based lenders. It may also indicate that the GDPR only modestly improved consumer confidence in technology firms, relative to FinTech companies whose business models depend more directly on transparent data usage and personal information flows. By contrast, the GDPR's positive and statistically significant effect on FinTech credit remains consistent and robust across all model variations.

6 Conclusions and Policy Implications

Digital financial services increasingly rely on the collection and analysis of personal data. When combined with algorithmic tools, these data allow technology firms to develop predictive credit models that may outperform traditional credit bureaus. However, such capabilities raise privacy concerns, including risks of misuse, identity theft, and discriminatory pricing. In response, governments have introduced legal frameworks to regulate data use and protect consumer privacy. Among these, the European Union's General Data Protection Regulation (GDPR) is one of the most comprehensive and influential.

This study empirically evaluates the impact of GDPR on the alternative credit market—comprising FinTech and BigTech lending—across 45 countries from 2013 to 2020. Using Difference-in-Differences and Synthetic Difference-in-Differences approaches and a range of robustness checks, I find that GDPR had a positive and statistically significant effect on FinTech and overall alternative credit. In contrast, the effect on BigTech credit is consistently positive but statistically insignificant across most specifications.

The results show that well-designed data regulations can support inclusive and trusted digital finance. Specifically, GDPR increased alternative credit in treated countries by approximately 1.08 to 1.75 percentage points. This suggests that privacy protections can enhance users' willingness to share data, especially in countries with high institutional trust and strong digital infrastructure. By reducing the perceived risks of data sharing, GDPR may have fostered greater engagement with digital lenders. However, the regulation's effect is attenuated in markets dominated by a few incumbent banks, underscoring how structural conditions shape regulatory outcomes.

The policy implications of these findings are multi-faceted. First, data regulation can expand credit access, provided it is accompanied by transparent enforcement and public trust. The evidence indicates that stronger data protections may increase users' willingness to share personal information, thereby broadening access to digital credit. Regulatory clarity and consistency ensure that firms align their data practices with consumer interests. Policymakers should therefore view privacy not merely as a compliance cost but as a strategic enabler of digital finance—particularly when supported by strong legal institutions and robust consumer protections.

Second, the structure of domestic banking markets influences how regulatory reforms play out. In highly concentrated systems, dominant incumbents may resist competitive entry or influence regulatory implementation, thereby muting the intended effects of privacy reform. In such contexts, privacy regulation alone may not be sufficient to open markets to new entrants. Complementary reforms that address structural barriers may be required to ensure data regulations translate into genuine market diversification. Third, complementary investments in digital infrastructure and data literacy are essential to ensure that regulatory gains translate into broad financial inclusion. Without widespread access to digital tools and user awareness of data rights, regulatory benefits may remain confined to already-connected segments of the population.

Fourth, while this study observes a significant response in FinTech and alternative credit, the effect on BigTech credit remains muted and statistically inconsistent. This suggests that general-purpose privacy frameworks may be insufficient to address the complexities introduced by platform-based finance.

Fifth, regulatory credibility hinges not on the announcement but on legal enactment and visible, enforceable implementation. Firms did not adjust their behavior in response to the announcement; instead, credit patterns shifted only after the regulation came into effect—and more decisively in jurisdictions with active enforcement. While implementation matters, enforcement is the essential mechanism through which regulation gains traction, as the credible threat of penalties anchors expectations and compels behavioral change.

Looking ahead, several avenues remain open for further investigation. One promising direction that requires further investigation is regulatory spillover. Though this study focuses on the effects of the EU block policy, digital credit markets are inherently cross-border. Researchers could examine whether regulatory mismatches across jurisdictions generate arbitrage opportunities or dampen the intended effects of data protection reforms. Furthermore, subsequent research may study the regulation's effect on credit allocation quality, default risk, or financial inclusion. Differences in enforcement intensity, consumer response, and institutional capacity across countries also present valuable variation for empirical exploration. Since this study centers on the immediate post-GDPR period, a natural extension would be incorporating the expanded data on the increasing enforcement efforts, institutional adaptation, and firm-level compliance practices. These developments offer a longer-run view into how data regulations evolve from formal enactment to operational impact.

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Appendices

Appendices

A GDPR

In 2016, the EU adopted the General Data Protection Regulation (GDPR) as Regulation (EU) 2016/679, which will be fully implemented in all EU countries by May 2018. It replaces the 1995 Data Protection Directive, adopted when the internet was in its infancy. Unlike an EU directive, the GDPR applies across all EU member states without requiring each country to transpose it into national law.

At the core of GDPR[14] are seven key principles—laid out in Article 5 of the legislation—designed to guide how people's data can be handled. The following are the seven principles of GDPR. (1). Lawfulness, fairness, and transparency: Processing must be lawful, fair, and transparent to the data subject. (2). Purpose limitation: You must process data for the legitimate purposes specified explicitly to the data subject when you collected it. (3). Data minimization: This principle ensures organizations don't overreach with the type of data they collect about people. You should collect and process only as much data as absolutely necessary for the specified purposes. (4). Accuracy: You must keep personal data accurate and up to date. (5). Storage limitation: You may only store personally identifying data for as long as necessary for the specified purpose. (6). Integrity and confidentiality: Processing must ensure appropriate security, integrity, and confidentiality (e.g., by using encryption). Personal data must be protected against "unauthorized or unlawful processing " and accidental loss, destruction, or damage. (7). Accountability: the data controller is responsible for demonstrating GDPR compliance with these principles. It can also include training staff in data protection measures and regularly evaluating data handling processes.

While GDPR arguably impacts data controllers and processors the most, the legislation is designed to protect individuals' rights. As such, GDPR lays out eight rights. The full GDPR rights for individuals are the right to be informed, the right to access, the right to rectification, the right to erasure, the right to restrict processing, the right to data portability, the right to object, and also rights around automated decision making and

[14]Source: https://gdpr.eu/what-is-gdpr/

profiling.

B Internet Searches for GDPR

Google searches for the General Data Protection Regulation show that there were few to no searches about the GDPR during its announcement year in 2016. Interest in the GDPR picked up starting in early 2018 and gained its peak popularity around its implementation in May 2018.

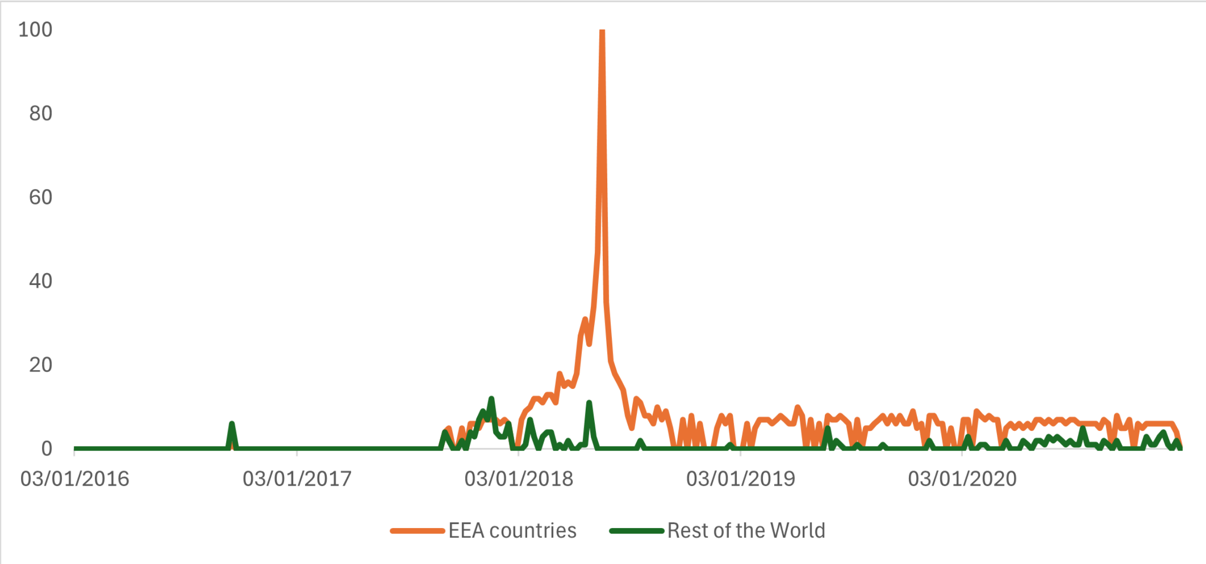

Figure B.1: Internet searches for GDPR ·

·The figure shows internet searches for the GDPR in the European Economic Area and the rest of the world. GDPR came into effect in May 2018. Numbers represent search interest towards GDPR relative to the highest point on the chart for EEA and the rest of the world between 2016 and 2020. A value of 100 is the peak popularity for GDPR compliance, and a value of 50 means that GDPR is half as popular. A score of 0 means there was not enough data for the regulation.

C Variable Descriptions

Table B1: Description and Source of Variables

Variable	Definition & Source of variable
FinTech credit	FinTech credit per capita (in USD). FinTech credit encompasses digital lending models such as peer-to-peer (P2P) lending, invoice trading, and other debt-based alternative finance mechanisms facilitated through online platforms. Data obtained from CCAF.
BigTech credit	BigTech credit per capita (in USD). It refers to loans issued by large technology companies whose core operations lie outside the financial sector but increasingly engage in financial intermediation directly or in partnership with financial institutions. Data obtained from Cornelli et al. (2020) and Frost et al. (2019)
Alternative Credit	is a lending activity by non-traditional financial intermediaries, and it is the sum of credit extended by FinTech and BigTech providers. These credit volumes are measured on a per capita basis in USD.
ggdppc	Annual percentage growth rate of Gross Domestic Product per capita based on constant local currency and divided by midyear population.
GDPpc	GDP per capita is gross domestic product divided by midyear population. Data are in constant 2015 U.S. dollars. Obtained from the World Bank WDI.
GDPpc_sqr	GDP per capita square is a quadratic form of GDP to capture the non-linear relationship between income level and credit development in the economy i at period t.
BankBranches	Bank branches per 100,000 adults and capture the reach of the banking sector through their subsidiary retail or main office that provides financial services to customers. Obtained from the World Bank WDI.
CrisisDummy	A dummy for whether a country had suffered a financial crisis since 2006, as defined by Laeven and Valencia (2018)
governance ind.	Governance indicator from the WB World Governance Indicators provide composite measures of institutional quality across six dimensions, including government effectiveness, regulatory quality, rule of law, and control of corruption. Each indicator is expressed on a standardized scale ranging from –2.5 (weak governance) to +2.5 (strong governance). The data are compiled annually by the World Bank.
Lerner_Index	Lerner Index measures the bank's market power in the banking sector markups and is normalized between 0 (perfect competition) and 1 (pure monopoly). Obtained from Global Financial Development Database (GFDD) and Igan et al. (2021).
Inflation	Rate of inflation are calculated as the annual change of the Consumer Price Index. It reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services. Data source: WDI

Table B1: Description of Variables (*continued*)

Variable	**Definition & Source of variable**
openness	Trade openness is the sum of exports and imports of goods and services measured as a percentage of GDP, and the data is obtained from WDI.
TotPopn	Total population, which counts all residents regardless of legal status or citizenship. The values shown are midyear estimates. Data obtained from WDI.
Popln growth.rate	Annual population growth rate expressed as a percentage. Data obtained from WDI.
trust_index	Proxied by the following three proxies. A percentage of year 15 and above population (i) who made or received a digital payment, (ii) who made a digital online merchant payment for an online purchase, and (iii) who used a mobile phone or the internet to buy something online. These three proxies are weighted and normalized into a trust index that ranges between 0 (no trust) and 1 (maximum trust). Data was obtained from the World Bank gender data portal.
Mob subscription	Mobile cellular subscriptions (per 100 people). It applies to all mobile cellular subscriptions that offer voice communications. Data comes from the International Telecommunication Union (ITU).
broadbnd subscr.	Fixed broadband subscriptions (per 100 people). Data comes from the ITU.
dom_private_credit	Domestic credit to the private sector (% of GDP). Financial resources provided to the private sector by financial corporations, such as loans, purchases of nonequity securities, trade credits, and other accounts receivable, establish a claim for repayment.
dom_credit	Domestic credit provided by the financial sector (% of GDP). It includes all credit to various sectors on a gross basis, with the exception of credit to the central government, which is net.
concentration	Assets of the five largest commercial banks as a share of total commercial banking assets. Measured as a percentage and data obtained from WDI.
regulatory_index	Index of bank regulatory stringency normalized between 0 (no regulation) and 1 (max regulation). The index is computed following Barth et al. (2004), Navaretti et al. (2018), and Cull et al. (2023) using the World Bank's Bank Regulation and Supervision Survey. The regulatory indices are activity restrictions, capital requirements, supervisory power, and ease of entry.

D Summary Statistics

Table B2: Basic Summary Statistics

	N	Mean	Min	Max	SD
FinTech Lending	360	3950.32	0	356832	26690
BigTech Lending	242	8123.95	0	668819	59912
Alternative Credit	360	9411.42	0	669973	64827
GDPpc growth	360	1.66	-12	23	4
GDP per capita	360	37181.67	5033	122114	20032
BankBranches	347	26.27	0	82	15
Fincial crisisDummy	360	0.53	0	1	0
LernerIndex_normalized	328	0.59	0	1	0
dom_private_credit	352	77.90	19	255	42
Provison_npl	309	56.96	15	283	30
dom_credit	84	111.64	23	391	99
bank_credit_private_GDP	344	75.29	19	183	37
Concentration	342	78.03	36	100	16
Comm.bank borrower	142	414.97	53	854	193
Non-int.income to tot.income	349	41.84	14	94	13
lending_rate	157	6.86	0	22	4
real interest rate	157	3.16	-12	12	3
Mobile subscription	352	118.95	69	164	17
broadband subscriptions	352	29.02	1	46	9
fixed_teleper100pep	352	31.30	1	61	14
Inflation	360	2.66	-3	39	4
Trade openness	360	106.92	23	382	65
Popln growth.rate	360	0.29	-2	4	1
Made_received_digtl paymnt	352	0.79	0	1	0
trust_index	352	0.87	-1	2	1
Bank regulatory_index	360	0.41	0	1	0

Source: Own computation

Table B3: Balance Test by Treatment Group

	N	Mean_Treated	Mean_Control	Difference
FinTech Lending	219	414.095	233.232	180.863
BigTech Lending	167	4285.610	4.242	4281.368**
Alternative Credit	219	4699.705	236.377	4463.328**
GDPpc growth	219	1.081	2.052	-0.970
GDP per capita	219	44924.386	41292.796	3631.591
BankBranches	213	28.229	30.143	-1.914
Lerner Index_normalized	198	0.359	0.587	-0.228**
dom_private_credit	213	119.687	89.382	30.305*
Provison_npl	190	20.195	50.181	-29.986**
dom_credit	13	343.394	139.353	204.041**
bank_credit_private_GDP	206	118.059	84.668	33.390**
Concentration	212	78.876	83.702	-4.826
Non-Performing Loan	212	1.011	8.006	-6.995**
capital adequacy	217	14.738	18.849	-4.111**
Z-Score	217	14.859	14.762	0.098
ROA	215	0.629	0.848	-0.219
Liquidity	189	26.564	34.529	-7.964
Margin	218	1.422	1.947	-0.526*
Non-int.income to tot.income	217	35.617	44.009	-8.391**
lending_rate	69	3.344	5.076	-1.731*
real interest rate	69	2.377	2.832	-0.455
Mobilesubscrper100people	219	107.489	122.880	-15.391**
broadbandper100pep	219	32.346	31.301	1.045
fixed_teleper100pep	219	43.156	35.142	8.013*
Inflation	219	0.946	1.586	-0.640
Trade openness	219	47.244	125.570	-78.326**
Population growth.rate	219	0.849	0.345	0.504*
Made_received_digtl paymnt	212	0.954	0.855	0.100**
trust_index	212	1.432	0.976	0.457**
Bank regulatory_index	219	0.321	0.285	0.036

This table reports summary statistics of country characteristics between 2013 and 2018 - before the GDPR intervention. The sample is split into treated and control groups. The treated group comprises all EEA countries, and the control group comprises the United States, Canada, Australia, and Japan. The column N, mean_treated, and mean_control denote the number of observations, the mean values of the variables in the treated and control groups, respectively. The column, Difference, is defined as the difference in the mean values of the variables in the treated and control groups.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B4: Countries Included in the Empirical Analysis

Countries			
Albania	Australia	Austria	Belarus
Belgium	Bosnia and Herzegovina	Bulgaria	Canada
China	Croatia	Cyprus	Czech Republic
Denmark	Estonia	Finland	France
Germany	Greece	Hungary	Iceland
India	Ireland	Italy	Japan
Kosovo	Latvia	Lithuania	Luxembourg
Malta	Moldova	Netherlands	Norway
Poland	Portugal	Romania	Russian Federation
Serbia	Slovak Republic	Slovenia	Spain
Sweden	Turkey	Ukraine	United Kingdom
United States			

E Derivation of the DiD Estimator for GDPR Impact on Alternative Credit

This section outlines the formal identification strategy underlying the Difference-in-Differences (DiD) approach used to estimate the causal effect of the GDPR regulation on alternative credit markets. Let AC_{0i} denote the volume of alternative credit in country i in the absence of stricter privacy regulation, and let AC_{1i} represent the volume under GDPR. The expected volume of alternative credit for country i in year t, absent the GDPR, is $E[AC_{0i} \mid t]$, while under GDPR it is $E[AC_{1i} \mid t]$. The treatment period t is binary, where $t = 0$ for years prior to 2018 and $t = 1$ for 2018 onward. The sample includes two groups of countries: those implementing GDPR (the treatment group) and those that did not adopt GDPR or GDPR-like regulations (the control group). Under the parallel trends assumption that in the absence of the policy intervention, the treated and control groups would have followed similar trends, the causal effect of GDPR (the treatment effect) can be estimated by δ, defined as:

$$\delta = (E[AC_{it}|i = EEA, t \geq 2018] - E[AC_{it}|i = EEA, t < 2018]) \\ - (E[AC_{it}|i = con, t \geq 2018] - E[AC_{it}|i = con, t < 2018]) \quad (2.4)$$

δ measures the counterfactual average, $E[AC_{0i}|i = EEA, t \geq 2018]$, that is, the expected alternative credit volume in the absence of GDPR for treated countries in the post-treatment period. Here, AC_{it} represents the volume of FinTech, BigTech, or combined alternative credit in country i at time t.

To express the model in functional form, suppose that

$$E[AC_{0i} \mid t] = \alpha_t + \gamma_i \quad (2.5)$$

represents the expected volume of alternative credit in the absence of GDPR.

Assuming the GDPR introduces a constant treatment effect δ, the outcome equation is specified as:

$$E[AC_{1i} \mid t] = E[AC_{0i} \mid t] + \delta = \alpha_t + \gamma_i + \delta \quad (2.6)$$

The observed volume of alternative credit for country i in year t, covering the period from 2013 to 2020, is modeled as:

$$AC_{it} = \alpha_t + \gamma_i + \delta w_{it} + \epsilon_{it} \quad (2.7)$$

where AC_{it} is the dependent variable denoting the volume of FinTech, BigTech, or total alternative credit; α_t are time fixed effects; γ_i are country fixed effects; and ϵ_{it} is an idiosyncratic error term with $E[\epsilon_{it} \mid t] = 0$. The variable w_{it} is an interaction term equal to 1 if both $\text{Post}_t = 1$ and $\text{Treated}_i = 1$. Here, Treated_i is a binary indicator equal to 1 for EEA countries subject to GDPR, and 0 otherwise. Post_t equals 1 for years $t \geq 2018$, and 0 before.

Adding a vector of time-varying covariates, X_{it}, along with time and country fixed effects to control for confounding influences, the baseline regression model is specified as:

$$\text{AC}_{it} = \beta_0 + \beta_1 \text{Post}_t + \beta_2 \text{Treated}_i + \delta(\text{Post}_t \times \text{Treated}_i) + X'_{it}\psi + \alpha_t + \gamma_i + \epsilon_{it} \quad (2.8)$$

where ϵ_{it} is the idiosyncratic error term.

F Derivation of the Synthetic DiD Estimator for GDPR Impact on Alternative Credit

This section outlines the Synthetic Difference-in-Differences (SDiD) methodology employed as a robustness check to validate the baseline DiD estimates. Developed by Arkhangelsky et al. (2021), SDiD integrates essential features of both Difference-in-Differences (DiD) and the Synthetic Control (SC) method. As with DiD, SDiD accommodates baseline trend heterogeneity between treated and control units. Like SC (Abadie et al., 2010), it constructs a weighted synthetic control group by matching pre-treatment outcomes and covariates to closely resemble the treated group.

SDiD's weighting approach mitigates reliance on the assumption of parallel trends and reduces sensitivity to model misspecification. SDiD also avoids common pitfalls in standard DID and SC methods– namely, an inability to estimate causal relationships if parallel trends are not met in aggregate data in the case of DiD and a requirement that the treated unit be housed within a "convex hull" of control units in the case of SC (Clarke et al., 2023). Empirically, Arkhangelsky et al. (2021) finds that the SDiD method competes with (or dominates) DID and SC in applications.

Consider a balanced panel of N countries observed over T time periods, where the outcome for unit i in period t is denoted by AC_{it}, and treatment status is given by $W_{it} \in \{0, 1\}$. The treatment variable $W_{it} = 1$ if country i is treated by time t, and $W_{it} = 0$ otherwise. The SDiD estimator requires at least two pre-treatment periods and excludes units that are always treated. Let the first N_{co} units (control countries) be never treated, and the remaining $N_{tr} = N - N_{co}$ units (treated countries) receive treatment after period T_{pre}.

Following the Synthetic Control approach, SDiD constructs unit weights $\hat{\omega}^{SDiD}$ to minimize the distance between treated and control units based on pre-treatment characteristics and outcomes: $||X_{\text{treat}} - X_{\text{control}}||$. The matrix X includes covariates and lagged outcomes. This weighting effectively localizes the two-way fixed effects (TWFE) estimator, emphasizing comparisons between units and time periods most similar to the treated group in the pre-treatment period (Clarke et al., 2023).

SDiD also incorporates time weights $\hat{\lambda}_t^{SDiD}$ to balance pre- and post-treatment periods.[15] These weights improve precision and reduce bias by down-weighting time periods that are poorly aligned with the post-treatment window. The inclusion of unit fixed effects serves two purposes: first, it enhances model flexibility and robustness; second, it captures persistent unobserved heterogeneity, which often explains substantial outcome variation.

Following Arkhangelsky et al. (2021), the average causal effect of the GDPR regulation, denoted by δ, is estimated using unit and time weights within a two-way fixed effects regression:

$$\left(\hat{\delta}^{SDiD}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \arg\min_{\delta,\mu,\alpha,\beta} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\delta\right)^2 \hat{\omega}_i^{SDiD} \hat{\lambda}_t^{SDiD} \right\} \tag{2.9}$$

where, δ represents the average treatment effect on the treated (ATT), estimated via a weighted least squares regression. The weights $\hat{\omega}_i^{SDiD}$ and $\hat{\lambda}_t^{SDiD}$ are optimally selected to balance treated and control units across units and time periods. μ is a constant, α_i are unit fixed effects, and β_t are time fixed effects.

[15] See Arkhangelsky et al. (2021) for full details on unit and time weight construction.

For comparison, the standard DiD estimator applies the same regression framework but assigns equal weights across all units and time periods:

$$\left(\hat{\delta}^{DiD}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \arg\min_{\delta,\mu,\alpha,\beta} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\delta\right)^2 \right\} \tag{2.10}$$

In contrast, the Synthetic Control (SC) estimator omits unit fixed effects and time weights but includes optimally chosen unit weights $\hat{\omega}_i^{SC}$:

$$\left(\hat{\delta}^{SC}, \hat{\mu}, \hat{\beta}\right) = \arg\min_{\delta,\mu,\beta} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu - \beta_t - W_{it}\delta\right)^2 \hat{\omega}_i^{SC} \right\} \tag{2.11}$$

There are several practical requirements for implementing the SDiD algorithm. First, the dataset must be a balanced panel, with complete observations on outcomes and treatment status for each unit across all time periods. Second, units treated from the outset of the study must be excluded, as they lack a pre-treatment period necessary for constructing a valid synthetic counterfactual. Third, a subset of units must remain untreated throughout the study period to serve as donor units in the synthetic control construction. Finally, for valid inference using bootstrap or jackknife methods, more than one treated unit is required (Arkhangelsky et al., 2021; Clarke et al., 2023).

G Pre-Treatment Trends in the Alternative Credit

This section presents the results of DiD Estimation when the control group consists of the United States, Japan, Canada, and Australia.

Table B5: Parallel Trend Assumption with Four Countries Control Group

	(1) FinTech credit	(2) BigTech credit	(3) Alternative Credit
Treat	-5.838***	-4.483*	-6.948***
	(1.513)	(2.398)	(1.757)
Post	0.653***	0.392*	0.616***
	(0.170)	(0.234)	(0.193)
Post*Treat	0.153	0.076	0.193
	(0.200)	(0.241)	(0.222)
Constant	5.060***	6.678***	6.171***
	(1.233)	(2.347)	(1.524)
Year FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Adj.R-squared	0.581	0.826	0.578
N	149	16	149

This table reports results for Equation (1.5) before the GDPR intervention (year $\leq$ 2018) and controls for country and year fixed effects. The result is a test for the parallel trend assumption. The dependent variable is the log of FinTech credit(column 1), BigTech credit(column 1), and alternative credit(column 3). The dummy Treat takes on a value of one if the country is in the treated group (EEA countries) and 0 for countries in the control group (United States, Canada, Australia, and Japan). The dummy post takes on a value of one after the GDPR was enacted in 2018. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

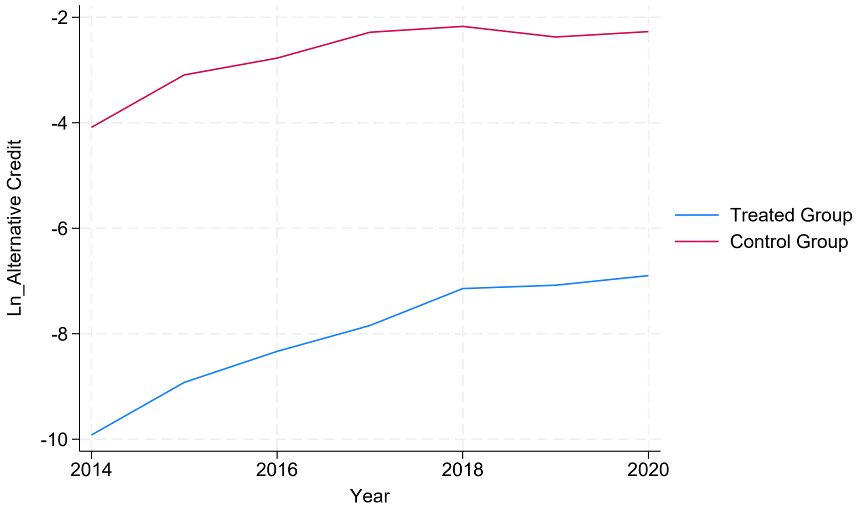

Figure B.2: Trends in Alternative Credit with Four Countries Control Group

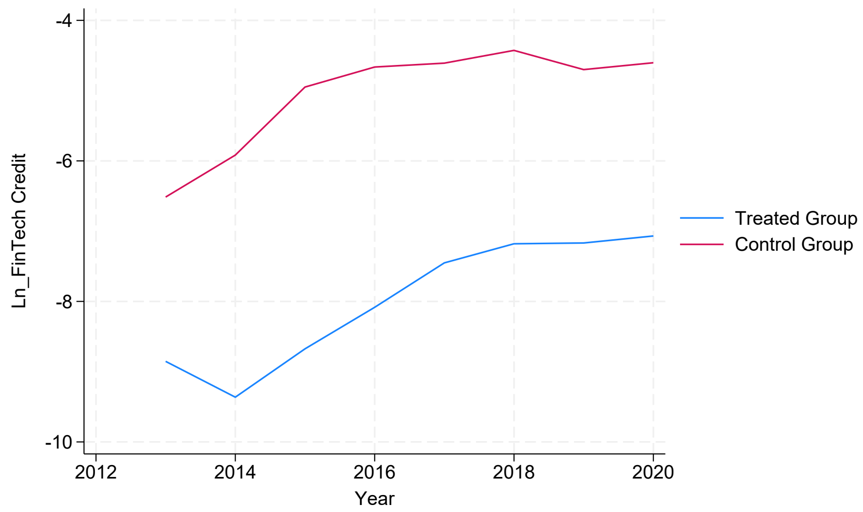

Figure B.3: Trends in FinTech Credit with Four Countries Control Group

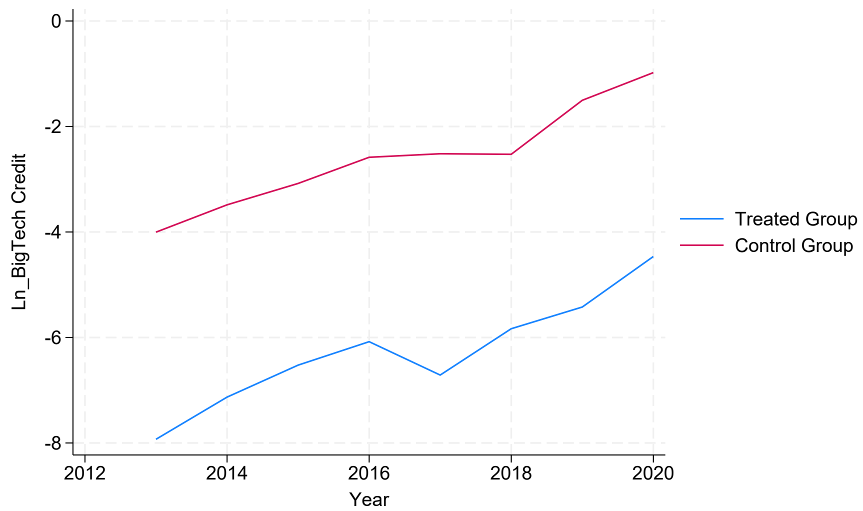

Figure B.4: Trends in BigTech Credit with Four Countries Control Group

Table B6: Placebo DiD Estimation with Four Countries Control Group

	(1) Alt.Credit	(2) FinTech Credit	(3) BigTech Credit
placebo_post	3.967***	3.968***	1.386**
	(0.440)	(0.437)	(0.603)
placebo_treat	-5.759***	-4.749***	-3.699***
	(1.365)	(1.254)	(1.248)
placebo_interaction	-0.334	-0.352	-0.189
	(0.356)	(0.349)	(0.904)
Constant	4.619***	3.615***	6.714***
	(1.241)	(1.115)	(1.938)
Year FE	Yes	Yes	Yes
IncomeGroup FE	Yes	Yes	Yes
Adj.R-squared	0.594	0.594	0.718
N	251	251	28

This table reports placebo results for Equation (1.5) and controls for country and year fixed effects by considering 2016 and 2017 as a post-intervention period. The dependent variable is the log of FinTech credit(column 1), BigTech credit(column 1), and alternative credit(column 3). The dummy Treat takes on a value of one if the country is in the treated group (EEA countries) and 0 for countries in the control group (United States, Canada, Australia, and Japan). The dummy post takes on a value of one for 2016 and 2017 and 0 otherwise. The results confirm no pre-treatment difference in the trends between the treated and the control groups.

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B7: DiD Estimation with Four Countries Control Group and Including both Post and Anticipation

	(1) AC_Antcptn	(2) AC_Antcptn_Post	(3) FC__Antcptn
Treated	-4.734***	-2.896**	36.005**
	(1.291)	(1.440)	(14.987)
Post	4.555	4.567	-0.594
	(3.341)	(3.320)	(0.829)
Post × Treated	1.890**	1.815**	2.171**
	(0.811)	(0.819)	(1.095)
Anticipation	5.299	5.280	-1.017***
	(3.332)	(3.313)	(0.179)
Anticipation × Treated	0.793	0.794	1.119
	(0.614)	(0.620)	(1.113)
Bank regulatory index	-6.612	-6.668	-1.456***
	(4.895)	(4.863)	(0.251)
Lerner Index	0.737	0.771	-0.233
	(0.638)	(0.636)	(0.425)
Mobile subscriptions	5.262**	4.879*	14.563*
	(2.522)	(2.544)	(7.852)
Bank Branches	-0.158	-0.192	2.979
	(0.533)	(0.530)	(2.141)
Trust index	1.885	2.087	2.365
	(1.967)	(1.962)	(3.237)
GDP per capita growth	0.114	0.079	0.289***
	(0.175)	(0.176)	(0.104)
GDP per capita	1.959	2.025	8.264***
	(1.915)	(1.930)	(0.835)
Advanced Economy	2.846***	2.794***	0.000
	(0.897)	(0.909)	(.)
Openness	1.374	1.304	-7.444**
	(1.105)	(1.133)	(2.994)
Constant	-56.356***	-56.780***	-1101.152***
	(15.372)	(15.262)	(415.154)
Year FE	Yes	Yes	NO
Region FE	Yes	Yes	Yes
Adj.R-squared	0.561	0.558	0.987
N	185	185	20

All regressors are lagged and expressed in natural logarithmic form, except for inflation and the dummy variables. The table reports results from estimating Equation 2.3. The dependent variables are the alternative credit-to-GDP ratio (Column 1), the FinTech credit-to-GDP ratio (Column 2), and the BigTech credit-to-GDP ratio (Column 3), winsorized at the 1% and 99% levels. *Treated* equals one for countries in the treated group (EEA), and zero for Canada, Australia, or Japan. *Post* equals one for 2018 onward. Governance indicators and population growth rates were estimated but not reported for brevity. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

H Robustness and Sensitivity Results

H.1 DiD Estimation with Japan, Canada, and Australia as a Control Group

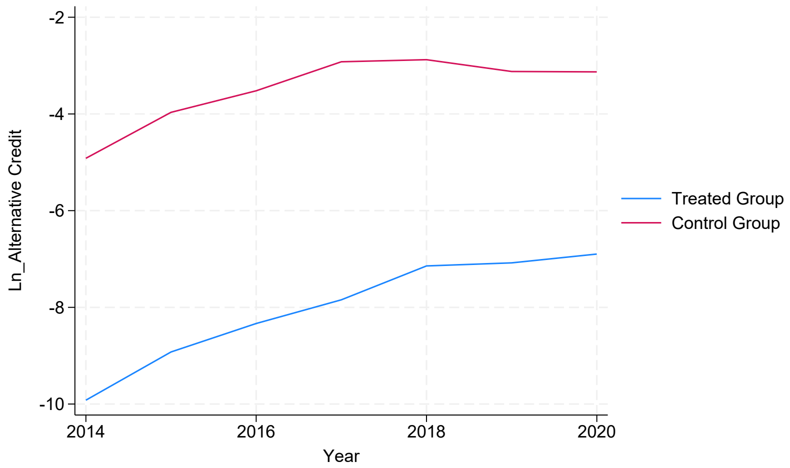

Figure B.5: Trends in Alternative Credit with Three Countries Control Group

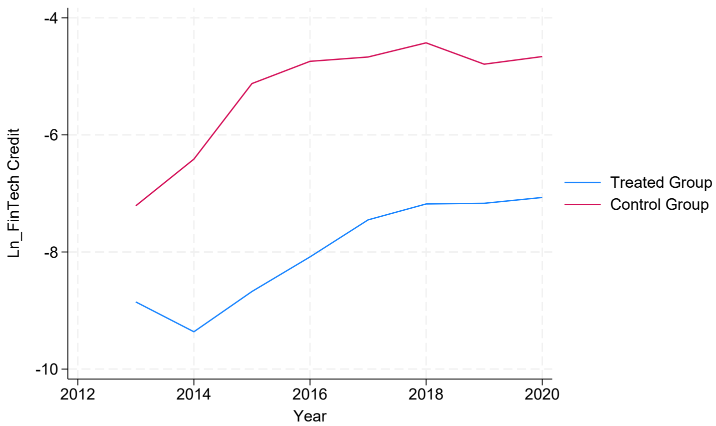

Figure B.6: Trends in FinTech Credit with Three Countries Control Group

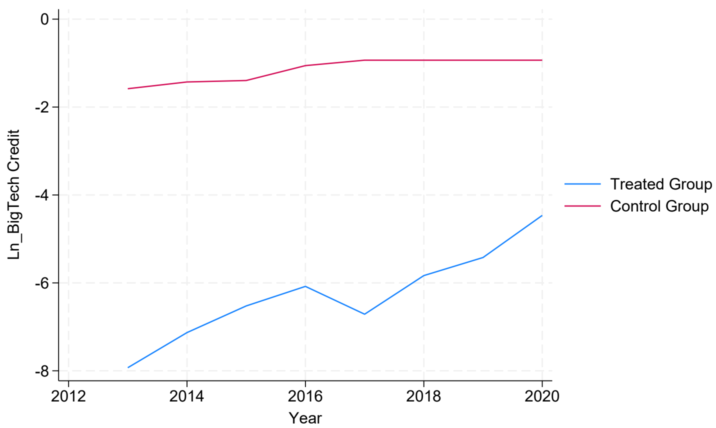

Figure B.7: Trends in BigTech Credit with Three Countries Control Group

Table B8: DiD with Three Countries Control Group

	(1) Alt.Credit	(2) FinTech Credit	(3) BigTech Credit
Treated	-2.515**	-2.175**	-6.404***
	(1.059)	(1.075)	(0.914)
Post	4.735*	4.592*	0.563
	(2.520)	(2.491)	(0.491)
Post × Treated	1.655***	1.609**	1.549*
	(0.562)	(0.638)	(0.874)
Lerner Index	0.687	0.701	-4.183
	(0.487)	(0.519)	(6.002)
Mobile subscriptions	2.065	2.200	2.261
	(2.074)	(2.123)	(2.976)
Bank Branches	0.129	0.195	3.312
	(0.431)	(0.426)	(2.532)
Trust index	1.798	2.285	3.672*
	(1.632)	(1.695)	(2.202)
GDP per capita growth	-0.062	-0.109	0.296
	(0.172)	(0.166)	(0.444)
GDP per capita	1.164	1.032	
	(1.363)	(1.367)	
Advanced Economy	2.423***	2.298***	0.000
	(0.856)	(0.842)	(.)
Inflation	0.332***	0.352***	0.117
	(0.064)	(0.066)	(0.268)
Population	-0.966	-1.207	0.000
	(2.132)	(2.170)	(.)
Constant	-37.183***	-34.857***	-14.576
	(11.820)	(12.058)	(20.967)
Year FE	Yes	Yes	NO
Region FE	Yes	Yes	Yes
Adj.R-squared	0.644	0.617	0.943
N	177	177	12

This table reports results for Equation (1.5). The dependent variables are the log of alternative credit (Column 1), FinTech credit (Column 2), and BigTech credit (Column 3), winsorized at the 1% and 99% levels. All regressors are lagged and expressed in natural logarithmic form, except for inflation and dummy variables. The variable *Treated* equals one for countries in the treated group (EEA) and zero for control countries (Canada, Australia, and Japan). The variable *Post* equals one for years from 2018 onward. Governance quality, banking regulation, and economic openness were included in the estimation for Columns 1 and 2 but are not reported. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

H.2 DiD Estimation with 13 countries as a control group

Table B9: Parallel Trend Assumption with Thirteen Countries Control Group

	(1) FinTech credit	(2) BigTech credit	(3) Alternative Credit
Treat	-0.761	-3.818**	-1.449
	(1.254)	(1.843)	(1.497)
Post	0.526***	0.120	0.419**
	(0.143)	(0.263)	(0.188)
Post*Treat	0.171	0.317	0.358
	(0.180)	(0.263)	(0.227)
Constant	-9.674***	-4.466**	1.138
	(1.077)	(1.768)	(1.305)
Adj.R-squared	0.534	0.318	0.507
N	152	22	154

This table reports results for Equation (1.5) before the GDPR intervention (year $\leq$ 2018) and controls for country and year fixed effects. The result is a test for the parallel trend assumption. The dependent variable is the log of FinTech credit to GDP ratio(column 1), BigTech credit to GDP ratio(column 1), and alternative credit to GDP ratio(column 3). The dummy Treat takes on a value of one if the country is in the treated group (EEA countries) and 0 for the thirteen countries in the control group. The dummy post takes on a value of one after the GDPR was enacted in 2018. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

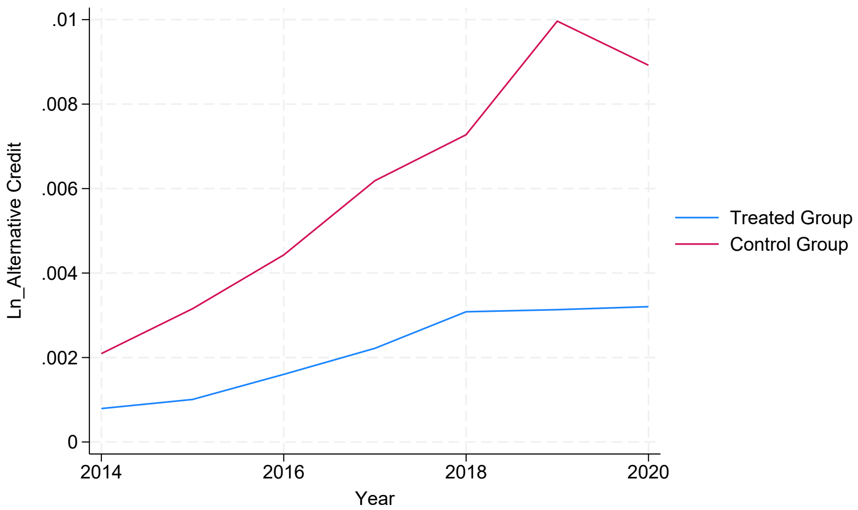

Figure B.8: Trends in Alternative Credit with Thirteen Countries Control Group

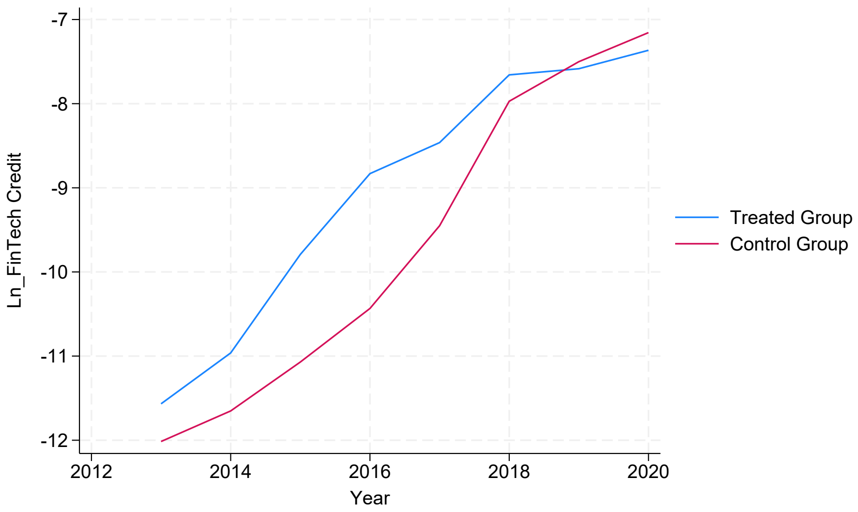

Figure B.9: Trends in FinTech Credit with Thirteen Countries Control Group

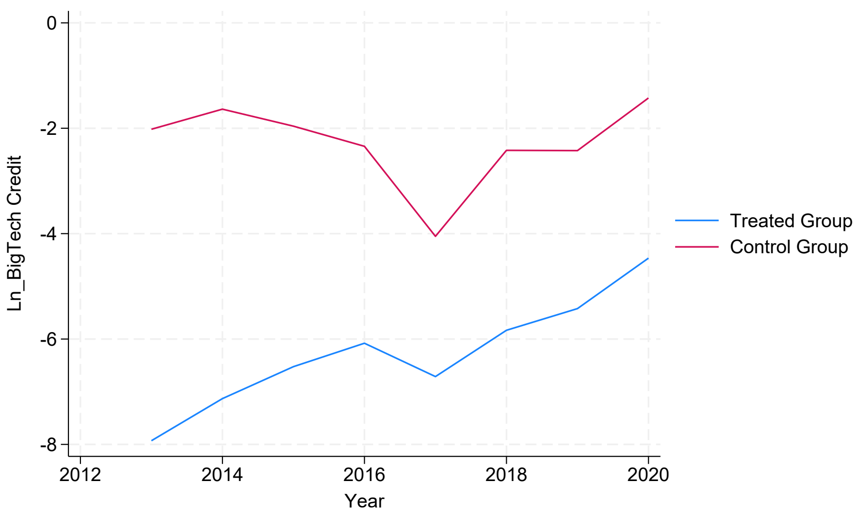

Figure B.10: Trends in BigTech Credit with Thirteen Countries Control Group

H.3 Synthetic DiD Estimation with 15 Countries Control Group

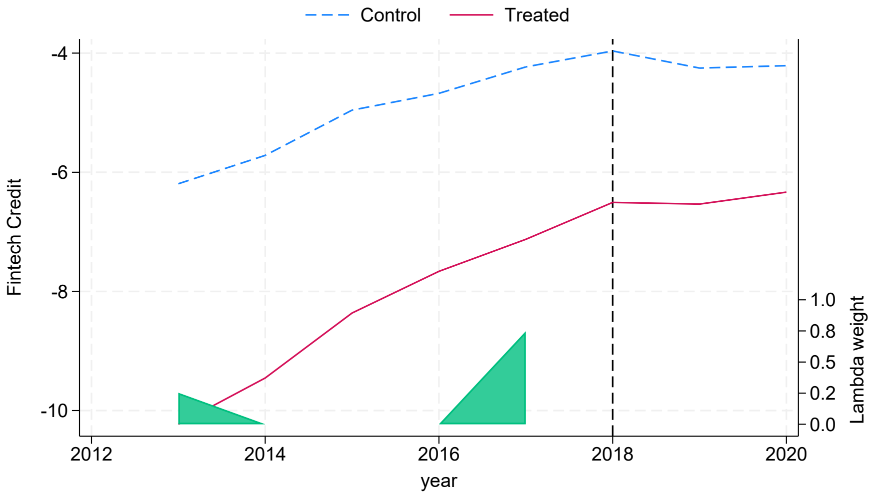

Figure B.11: Synthetic DiD Trends in FinTech Credit

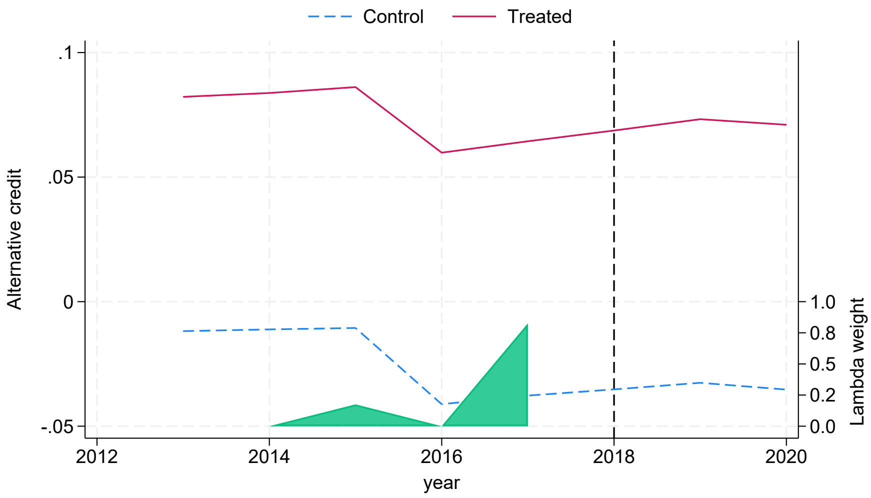

Figure B.12: Synthetic DiD Trends in Alternative Credit

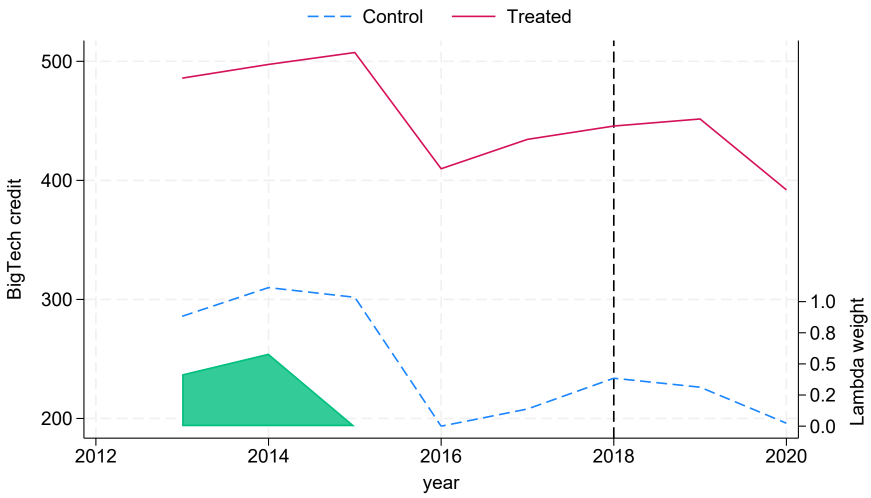

Figure B.13: Synthetic DiD Trends in BigTech Credit

H.4 Entropy Balancing and DiD

Table B10: Covariate Balance Before and After Entropy Balancing

Covariate	Treated		Control (Unweighted)		Control (Weighted)	
	Mean	Variance	Mean	Variance	Mean	Variance
Regulatory index	0.176	0.084	0.130	0.073	0.174	0.088
Lerner index	0.598	0.116	0.364	0.150	0.592	0.169
GDP per capita growth	0.393	1.287	0.205	0.201	0.386	0.111
Inflation	1.500	2.078	1.074	1.552	1.487	1.204

The table reports covariate balance before and after entropy balancing, based on the pre-treatment sample (years prior to 2018). Treated units correspond to EEA countries; control units are non-EEA advanced economies. All covariates are lagged.

Table B11: Entropy-Balanced DiD Estimates

	(1) Alt. Credit	(2) FinTech Credit	(3) BigTech Credit
Treated	-2.704***	-2.481***	-5.781***
	(0.426)	(0.349)	(0.566)
Post	6.520***	5.951***	0.383
	(2.026)	(1.936)	(0.694)
Post × Treated	1.608***	1.400***	0.378
	(0.413)	(0.392)	(0.972)
Bank regulatory index	-8.947***	-7.894***	1.872**
	(2.979)	(2.769)	(0.724)
Learner Index	0.316	0.432	0.964
	(0.403)	(0.383)	(0.733)
GDPpc growth	-0.071	-0.181	1.366**
	(0.208)	(0.188)	(0.597)
Inflation	0.169	0.141	-0.027
	(0.126)	(0.111)	(0.167)
Advanced Economy	3.005***	2.607***	0.000
	(0.571)	(0.459)	(.)
Constant	-8.973***	-8.642***	-2.165***
	(1.044)	(0.987)	(0.374)
Year FE	Yes	Yes	Yes
Income Group FE	Yes	Yes	Yes
Adj. R^2	0.480	0.537	0.903
N	193	193	26

This table reports entropy-balanced DiD estimates of GDPR's impact on alternative, FinTech, and BigTech credit volumes. The dependent variables in Columns (1)–(3) are the log of alternative credit, FinTech credit, and BigTech credit, respectively. Entropy balancing is applied to pre-treatment periods to reweight the control group such that key covariates match the treated group on their first moments. All regressors are lagged and expressed in natural logarithmic form, except for inflation, growth rate, and the dummy variable for advanced economies. The model corresponds to Equation 2.1 and includes year and income group fixed effects. Coefficients on GDP per capita level and mobile subscriptions are omitted in the reporting for brevity. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.