Bachelor Thesis

The impact of P2P financing on non-bank lender growth and profitability

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/Markuss Strižko/ /Tomass Vilks/

Date

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Abstract

This thesis examines how peer-to-peer (P2P) platform financing affects the growth and profitability of non-bank lenders in the Baltic States. The study compares firms that use P2P financing to those that rely on more traditional funding sources.

Using a staggered Difference-in-Differences (DiD) methodology, the research analyzes key performance indicators such as Return on Equity (ROE) and year-over-year Total Asset growth. The analysis draws on firm-level data across Latvia, Lithuania, and Estonia.

Findings reveal statistically significant portfolio growth (79–98%) for non-bank lenders adopting P2P financing, measured by Total Asset growth, establishing these platforms as effective tools for rapid scaling in markets like the Baltics. While profitability initially declines due to integration costs, ROE typically recovers within a year as P2P-sourced loans generate revenue. Both growth and profitability gains diminish after three years, likely as mature firms transition to cheaper financing (e.g., bonds, bank partnerships).

The study underscores P2P's viability for short-term growth but highlights profitability's dependence on strategic timing and execution. By analyzing the under-researched Baltic fintech sector, it provides empirical evidence of P2P's dual impact: immediate asset expansion and delayed profitability recovery. These insights advance fintech financing research and offer actionable guidance for stakeholders navigating evolving credit markets.

1. Introduction

The non-bank lending industry across the Baltic States—Latvia, Estonia, and Lithuania—has undergone significant growth over the past decade, becoming an integral part of their respective financial systems. These lenders, which operate outside of traditional banking frameworks, have attracted increasing attention due to their flexibility, digital-first strategies, and rapid market penetration (European Commission, 2023).

In Latvia, the non-bank lending sector has become one of the most dynamic in Europe. Latvian lenders have adopted innovative capital-raising methods, such as peer-to-peer (P2P) platforms, diverging from more traditional funding routes like bank loans or IPOs. These platforms have enabled non-bank firms to raise capital directly from individuals and retail investors, illustrating the agility and resourcefulness of the sector (Mazure, 2017; FintechLatvia, 2023).

As shown in Figure 1, the total credit portfolio of consumer credit providers in Latvia has grown substantially—from €350.15 million in mid-2013 to over €1.13 billion by mid-2024. This upward trend underscores not only consumer demand but also the maturity of the sector, especially in terms of financial innovation and regulatory compliance (FintechLatvia, 2023).

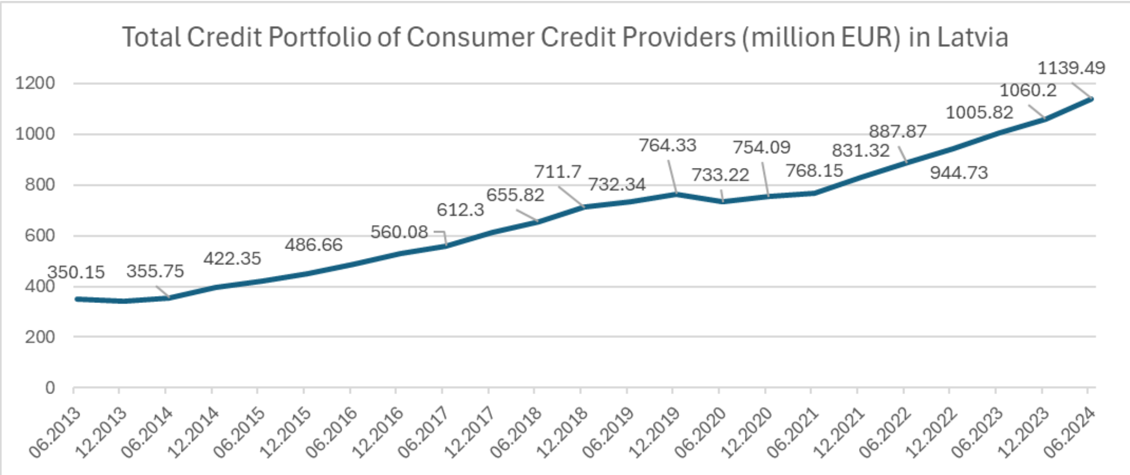

Figure 1. Total Credit Portfolio of Consumer Credit Providers in Millions EUR. Data source: Consumer Rights Protection Centre of Latvia (2024). Retrieved from [*https://www.ptac.gov.lv/lv/media/4852/download?attachment*](https://www.ptac.gov.lv/lv/media/4852/download?attachment)

Estonia has experienced a similar trend, with a steady rise in the issuance of consumer credit by non-bank entities. While bank-associated creditors still dominate the market, non-bank lenders represent a growing share of total credit issuance. These lenders are especially attractive to consumers seeking faster application processes, more flexible underwriting, and broader access to credit for those underserved by traditional banks (Bank of Estonia, 2024). Figure 2 highlights the balance of consumer credits issued in Estonia, distinguishing between bank-affiliated and non-bank creditors. The data illustrates a consistent increase in total lending activity, with non-bank lenders gradually capturing a larger slice of the credit market.

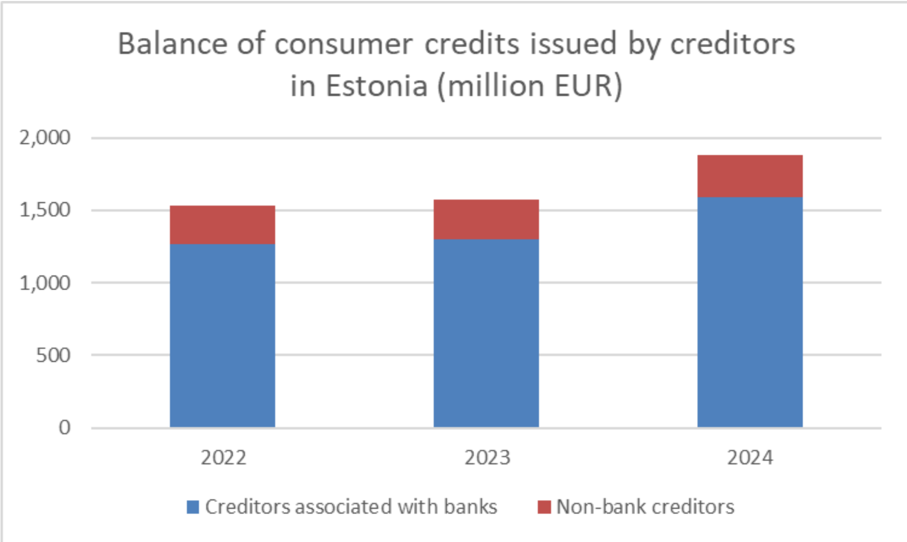

Figure 2. Balance of consumer credits issued by creditors in Estonia. Source: Bank of Estonia (2025). Retrieved from https://statistika.fi.ee/fistar/#/en/p/4270/r/4418/4147

In Lithuania, the non-bank lending landscape is characterized by the growing assets of financial corporations engaged in lending. These institutions have benefited from a supportive regulatory framework and advancements in digital lending technologies. Non-bank lenders in Lithuania often target underbanked populations and small businesses, offering a streamlined alternative to traditional bank loans (Bank of Lithuania, 2023). Figure 3 presents the total value of loans held by financial corporations involved in lending, which has risen notably from Q1 2015 to Q3 2024. This growth indicates increased borrower reliance on alternative credit providers and the resilience of the sector even during economic fluctuations.

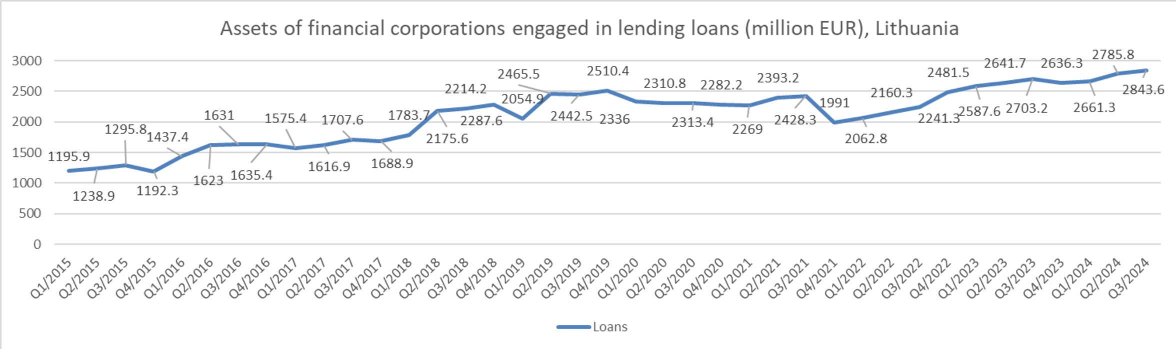

Figure 3. Assets of financial corporations engaged in lending loans (millions EUR), Lithuania. Source: Bank of Lithuania (2025). Retrieved from https://www.lb.lt/en/assets-of-financial-corporations-engaged-in-lending?ff=1&date_interval%5Bfrom%5D=2015-Q1&date_interval%5Bto%5D=2024-Q3

While the non-bank lending sector in the Baltics initially attracted users through its convenience and speed, it has since evolved. Today, it is marked by heightened regulatory oversight and improved consumer protections. Authorities such as Latvia's Financial and Capital Market Commission (FCMC), Bank of Latvia, Estonia's Financial Supervision Authority (EFSA), Bank of Estonia, and the Bank of Lithuania have introduced rules to encourage transparency, responsible lending, and market stability (European Banking Authority, 2023; Mazure, 2017; FintechLatvia, 2023).

Overall, the rise of non-bank lenders across the Baltic States reflects a broader shift in consumer credit behavior, with borrowers increasingly embracing digital-first and decentralized financial services. The continued development of this sector will likely play a key role in shaping the future of finance in the region (OECD, 2022).

This research evaluates the efficiency of peer-to-peer (P2P) platform refinancing as a primary capital attraction tool for Baltic non-bank lenders. Specifically, it investigates whether companies utilizing this method exhibit superior growth and profitability compared to those relying on more traditional financing strategies. Key indicators assessed include portfolio expansion, balance sheet size, and return on equity (ROE).

P2P platform refinancing has emerged as a relatively recent yet transformative financing strategy for non-bank lenders in Baltics. Unlike institutional loans or public offerings, P2P platforms offer low entry barriers, enabling broader participation from retail investors. This accessibility has contributed to the rapid adoption and expansion of such platforms across the sector (FintechLatvia, 2023).

Moreover, the increasing transaction volumes and consistent annual milestones achieved by P2P platforms highlight their growing role within the alternative finance landscape. These developments suggest that P2P lending is not only a viable funding source but a potentially dominant strategy for firms seeking scalability and operational agility.

This study is grounded in foundational theoretical frameworks, including Modigliani and Miller's (1958) cost of capital theory and Rajan and Zingales' (1995) capital structure model. These frameworks provide a robust lens through which to analyze how financing choices impact firm performance, particularly in non-traditional financial institutions (Rajan & Zingales, 1995). Additionally, recent research has emphasized the dual role of P2P lending as both a substitute for and complement to conventional credit channels, enriching the debate on capital efficiency and market positioning (Tang, 2019; Buchak et al., 2018).

The non-bank lending sector, while fostering financial inclusion and expanding credit access, also mirrors global trends seen in the evolution of shadow banking. These institutions—operating outside of conventional regulatory frameworks—have enabled credit growth in underserved regions, particularly rural or economically marginalized areas (Mazure, 2017). However, their growing influence also brings challenges such as liquidity management, credit risk, and the need for adaptive regulatory frameworks (Buchak et al., 2018; European Banking Authority, 2023).

This thesis aims to fill a critical research gap by applying established capital structure theories to a rapidly evolving fintech environment. By focusing on P2P-based strategies, it seeks to identify the most effective approaches for sustainable and profitable growth among non-bank lenders. The anticipated findings will offer actionable insights for industry practitioners, regulators, and academics, contributing to improved policymaking and strategic development within Baltic's financial sector—and potentially across similar markets in Europe.

To address this research gap, the thesis aims to evaluate the efficiency and effectiveness of P2P lending platforms as primary capital attraction mechanisms for Baltic non-bank lenders. Specifically, this study seeks to answer the following research questions:

1. Do Baltic non-bank lending companies utilizing P2P platform refinancing demonstrate superior portfolio growth compared to companies relying on alternative financing strategies?
2. Do Baltic non-bank lending companies utilizing P2P platform refinancing exhibit higher return on equity (ROE) compared to those employing other capital attraction methods?

In a rapidly globalizing and digitally transforming financial ecosystem, understanding the drivers of success for non-bank lenders is more important than ever. This research therefore not only explores the operational advantages of P2P capital attraction methods but also their broader socioeconomic implications, particularly with regard to financial inclusion, resilience, and market stability.

2. Literature review

This part of the thesis is structured in two parts: in the first one authors provide background information on the relevant topic while on the second part authors review specific literature relating to the research problem. As authors we believe that by including a background information section, the importance of the nonbank sector can be better understood and allows us to justify our research.

2.1. Background information

It is well known that following standard microeconomic theory, after a financial crisis or instability, lenders and banks specifically will reduce their loan issuances, whether due to increased risk aversion or higher interest rates. Rauning et al. (2017) build on this by finding that following uncertain economic situations, not necessarily financial crisis, banks will slow down and reduce their lending. This aligns with Delis et al. (2014) work, which discovers that even when consumers and analysts feel anxious about economic situations, loan issuance will be reduced, despite the economy not being in recession. This consistent pattern of reduced lending during periods of uncertainty demonstrates the traditional banking sector's inherent procyclical nature.

The conservative approach by traditional banks, however, has created opportunities for alternative lending companies. While banks might issue fewer loans during crisis, instability, or anxious periods, the inverse relationship emerges when examining non-bank lenders. Gopal and Schnabl (2022) find that following the 2008 financial crisis, when banks lowered their lending, non-bank lenders offset the downturns by increasing their activity and capturing market share in small enterprise loans. Their research demonstrates that this expansion was one of the crucial factors that contributed to the recovery from the financial crisis. It is important to note that academic sources disagree whether this relationship functions as a substitute or a complement. Recent research by Wang et al. (2023) has reached a consensus that this relationship primarily acts as a complement to traditional banking. However, they note that a substitution effect becomes possible when bank credit supply is insufficient for the underlying community's needs.

The initial rise of non-bank lending started even before 2008 financial crisis; their first success came from the ability to exploit the fact that they do not face the same stringent regulations as banks do. Chen et al. (2023) study confirms it, finding that non-bank lenders enjoyed a steady rise after regulatory changes affecting banks in 1990s. Even more so, a study by Chernenko et al. (2022) shows that non-bank lenders originate loans to companies with negative EBITDA and high debt/EBITDA ratio, given that for banks to do the same would be too costly.

This regulatory advantage became even more pronounced during and after the financial crisis. The 2008 crisis exacerbated the situation, since banks faced a lot more scrutiny and were forced to follow even stricter regulation, non-bank lenders swooped in and enjoyed success. Buchak et al. (2018) conclude that there can be found a positive relationship between higher regulation and higher non-bank lender activity, especially in segments such as low income and minority borrowers. They also note that in particular fintech lending grew because of their technological prowess, both the ability to set better rates by utilizing secondary data acquired during application and the ease of origination.

As with each novel topic, especially in this case academic research varies, and in some parts contradicts each other. Berg et al. (2022) note that empirical findings so far are scarce, we don't fully understand all the underlying factors affecting such type of lending. Of course we can draw some conclusions from already done research, but they should be taken with a grain of salt given that factors across markets such as regulation, borrower preferences and more, differentiate the results.

2.2. Peer-to-peer lending business model origins and development

The evolution of digital lending has significantly transformed the financial landscape over the past two decades. Peer-to-peer (P2P) lending emerged in the early 2000s as a direct alternative to traditional bank financing, primarily driven by the need for simplified and accessible credit. Early P2P lending platforms, such as Zopa in the United Kingdom, created a streamlined, online marketplace that connected borrowers directly with individual investors, removing conventional banking intermediaries. Investors provided funds directly to borrowers, earning returns based on the interest rates charged, while borrowers benefited from quicker approvals, lower administrative hurdles, and potentially more favorable rates compared to traditional financial institutions (Milne & Parboteeah, 2016; Serrano-Cinca & Gutiérrez-Nieto, 2014).

With increased market complexity, regulatory requirements, and the need for enhanced risk management, the structure of P2P lending evolved into a more sophisticated, dual-intermediary system. Under this contemporary model, a specialized lending company (often termed loan originator) initially evaluates borrower creditworthiness, performs detailed risk assessments, and originates the loan from its own balance sheet. After disbursing funds to borrowers, these loans are then refinanced through independent digital platforms, creating a distinct separation between origination and investment processes (Claessens, Frost, Turner, & Zhu, 2018; Bachmann et al., 2021).

Today’s P2P lending platforms, exemplified by major marketplaces such as Mintos, Twino, and Esketit, aggregate loans from numerous loan originators, allowing investors to purchase fractional shares in a diverse range of consumer loan products. Investors earn returns from interest repayments by borrowers, whereas platforms generate revenue primarily from fees associated with listing loans, loan servicing, investor management, and facilitating transactions.

The intermediary role of these platforms not only increases transparency but also significantly broadens market liquidity and accessibility for retail investors (Mintos, 2023; Twino, 2023; Esketit, 2023). It is important to note that platforms like Mintos, Twino, Esketit, and similar marketplaces typically hold different regulatory licenses than traditional crowdfunding firms, reflecting their unique intermediary role and operational complexity.

Additionally, modern P2P lending platforms employ robust risk management mechanisms. Common practices include buy-back guarantees, where loan originators pledge to repurchase delinquent loans, usually after 30 to 90 days of missed payments. Platforms also maintain dedicated reserve or provision funds to cover potential loan defaults, reducing investor risk exposure. Moreover, by offering diversified investment portfolios spanning multiple loans, loan originators, and geographic regions, these platforms further mitigate concentration risks and enhance investor confidence and overall market stability (Mintos, 2023; Esketit, 2023).

2.3. Regulatory Provisions for P2P Platforms

Peer-to-peer (P2P) lending platforms in the Baltic States fall under the Markets in Financial Instruments Directive II (MiFID II), a comprehensive European regulatory framework introduced by the European Union in 2018 (European Securities and Markets Authority (ESMA), 2018). MiFID II aims to regulate financial markets, enhance investor protection, and increase transparency across financial institutions and investment firms. Under this directive, P2P lending platforms are supervised by national central banks, ensuring adherence to stringent operational standards and consumer safeguards.

Investor motivations for participating in P2P platforms include the potential for higher returns compared to traditional financial instruments, portfolio diversification, and access to investment opportunities previously reserved for institutional investors. Licensing frameworks under MiFID II enforce rigorous transparency measures, robust risk management practices, capital adequacy requirements, and detailed consumer disclosures. Additionally, platforms must perform suitability and appropriateness assessments for investors, ensuring investment products align with investors' risk profiles and financial knowledge. MiFID II also imposes comprehensive reporting and disclosure obligations, including regular financial statements, detailed information on default rates, and clear investment risk disclosures.

Enforcement of MiFID II compliance is actively conducted by national central banks, which regularly audit platform operations, monitor adherence to regulatory requirements, and apply sanctions or penalties for non-compliance. These stringent enforcement mechanisms enhance investor confidence and ensure that platforms maintain high standards of operational integrity and consumer protection.

2.4. Non-bank Lenders in the Baltic States: Regulatory Framework, Business Model, and Funding Sources

Non-bank lenders are financial institutions that provide credit and financing services without holding a banking license. They typically offer consumer loans, payday loans, installment loans, and other financial products directly to individuals. Unlike traditional banks, these entities usually operate with fewer regulatory burdens and have more flexible lending criteria, thus playing a critical role in providing alternative access to finance, particularly to segments underserved by traditional banking institutions (European Central Bank, 2021).

In the Baltic States—Estonia, Latvia, and Lithuania—non-bank lenders must obtain a specialized license to operate legally and issue consumer loans. This licensing requirement ensures regulatory oversight aimed at safeguarding consumer interests and maintaining overall market stability (Bank of Lithuania, 2020; Estonian Financial Supervision Authority, 2019; Bank of Latvia, 2023).

In Estonia, non-bank consumer lenders are required to secure the "Laenuandmise luba" (Money Lending License) as mandated by the Estonian Money Lending Act. Established in 2008, this regulatory framework imposes strict conditions on operational transparency, capital adequacy, comprehensive risk management practices, and explicit consumer disclosures (Estonian Financial Supervision Authority, 2016).

Similarly, Latvia mandates that non-bank lenders obtain a Money Lending License regulated by the Bank of Latvia. Since 2023, when the Financial and Capital Market Commission (FKTK) was integrated into the Bank of Latvia, licensing and supervision have become centralized within the national bank. This licensing regime, initially implemented following legislative reforms in the early 2000s, emphasizes consumer protection, clear disclosure of interest rates, and operational reliability, with stringent supervision to ensure compliance with comprehensive risk management standards (Latvijas Banka, n.d.).

Lithuania's regulatory environment also necessitates non-bank lenders to possess a Money Lending License, overseen by the Bank of Lithuania. Since the regulatory reforms introduced in the early 2010s, the Lithuanian licensing framework has emphasized consumer protection, financial stability, and operational transparency among lending institutions (Bank of Lithuania, 2020).

2.5. Business Model and Operations

Non-bank consumer lenders in the Baltic region generally operate through streamlined, technology-driven business models that leverage digital platforms to reach consumers quickly and efficiently. Their lending operations typically involve simplified application processes, rapid loan approval, and minimal paperwork. This accessibility and efficiency allow them to cater to consumer segments often underserved by conventional banks, such as individuals with limited credit histories or lower income levels (European Central Bank, 2021).

Revenue for non-bank lenders primarily derives from the interest rates and fees charged on loans issued. Due to higher risk profiles, interest rates tend to be higher than those offered by traditional banks. Non-bank lenders often utilize advanced credit-scoring techniques and data analytics to assess borrower risk accurately, thus managing potential defaults effectively (World Bank 2023).

2.6. Most Common Funding Practices of Non-Bank Lenders

Worldwide, both traditional and evolving practices characterize how non-bank lenders secure funding for their operations. Historically, the most conventional forms of funding have included equity capital and private loans, often sourced from venture capitalists, private equity funds, or high-net-worth individuals. These financing methods are especially common during the initial stages of firm development or in specialized lending markets with limited access to public funding channels (Ewens, Nanda, & Rhodes-Kropf, 2022).

A widely used traditional channel also includes bank financing, where non-bank lenders obtain credit facilities or warehousing lines from banks to fund loan origination. Despite regulatory separation, banks frequently act as upstream funders, especially when constrained by capital or risk exposure regulations (Frost et al., 2019).

Global trends have increasingly shifted toward market-based funding models, particularly through the issuance of asset-backed securities (ABS) and collateralized loan obligations (CLOs). These instruments allow lenders to securitize pools of receivables and sell them to institutional investors, thereby recycling capital and enabling further lending (Plantin, 2015). This trend is especially prominent in developed financial markets such as the United States and the European Union, where deep capital markets and investor appetite for structured credit support such practices.

Corporate bond issuance has also become a significant funding tool among larger non-bank financial institutions, offering access to lower-cost capital through capital markets. This is particularly relevant in low-interest-rate environments, where fixed-income investors seek yield from non-traditional sources (Adrian, Ashcraft, & Cetorelli, 2013).

Another increasingly relevant trend is the strategic affiliation of non-bank lenders with institutional investors, private credit funds, or technology firms. These affiliations may involve joint ventures, funding partnerships, or servicing arrangements, offering operational leverage and improved funding stability (Pozsar, 2014). In emerging markets, hybrid models involving fintech platforms and bank partnerships have emerged as dominant funding strategies, especially in regulatory environments that favor indirect intermediation.

Overall, the funding architecture of non-bank lenders has grown more diverse and sophisticated, reflecting a broader shift from relationship-based financing to structured, securitized, and capital markets-oriented models.

Given the profit-seeking nature of non-bank lenders and the increasing availability of peer-to-peer (P2P) lending platforms as an alternative funding route, we propose a testable hypothesis to evaluate the performance impact of these platforms. The assumption is that companies act rationally to maximize returns, and therefore, their choice of capital acquisition method should correlate with performance outcomes.

2.7. Review of relevant sources

Building on the previous sections, which examined the development, regulation, and funding of non-bank lenders, this part of the literature review focuses on existing academic work concerning how financing decisions influence the performance of financial institutions. While non-bank lending has seen rapid growth in recent years—particularly through innovative channels like peer-to-peer (P2P) platforms—academic research specifically addressing financing strategies in this sector remains relatively limited. To construct a strong theoretical foundation for our study, we draw on broader literature related to financial institutions, especially banks, while carefully acknowledging the structural differences in regulation, capital access, and technology use that set non-bank lenders apart.

One major research stream investigates the impact of loan growth on institutional performance and stability. The findings here are nuanced. Köhler (2015) reports that rapid loan growth can increase institutional risk, especially when such growth deviates from historical trends. Similarly, Clair (1992), in a study of Texas banks, found that high loan growth often precedes a deterioration in loan quality. Foos et al. (2010) also conclude that excessive loan expansion can lead to financial instability, underscoring the risks institutions face when growing their portfolios too aggressively.

A second body of literature explores the relationship between capital structure and institutional performance. Siddik et al. (2017) observe that a higher reliance on debt can enhance profitability in developing markets, though the benefits tend to diminish during times of financial distress. The theoretical underpinnings for these observations are well-established. For example, Berger and Bouwman (2013) analyze how capital levels influence bank performance in both stable and crisis periods, while Diamond and Rajan (2000) explain how financial institutions manage the trade-off between lending capacity and financial fragility through capital structure decisions.

The foundational work by Modigliani and Miller (1958) posits that under ideal conditions, a firm's value is unaffected by its capital structure. However, empirical studies often challenge this assumption. Berger (1995), for instance, finds that higher capital ratios are generally associated with stronger earnings in banking institutions, suggesting that capital structure decisions do, in fact, matter in practice.

Despite the insights provided by these studies, the vast majority focus on traditional banking institutions. There remains a notable gap in the literature when it comes to understanding how financing decisions affect the performance of non-bank lenders. Given the distinct regulatory environments and capital sourcing strategies—such as the increasing use of P2P lending platforms—it is insufficient to assume that conclusions drawn from traditional banking studies can be directly applied to this emerging sector.

This gap presents a compelling opportunity for further research. The literature reviewed highlights several key points that inform our hypothesis. First, non-bank lenders, unlike traditional banks, operate with fewer regulatory constraints, allowing them to adopt more flexible and innovative funding models, such as P2P platforms

(Buchak et al., 2018; Chen et al., 2023). These platforms enable non-bank lenders to access diverse funding sources, including retail and institutional investors, which can enhance liquidity and support portfolio expansion (Claessens et al., 2018; Mintos, 2023). Second, the technological advantages of P2P platforms, such as streamlined loan origination and advanced risk assessment, allow non-bank lenders to efficiently target underserved market segments, potentially leading to higher portfolio growth (Gopal & Schnabl, 2022; Bachmann et al., 2021). Third, the ability of non-bank lenders to complement traditional banking, particularly during periods of reduced bank lending, suggests that their funding strategies may contribute to greater resilience and profitability (Wang et al., 2023).

Drawing on these insights, we propose the following core hypothesis: Non-bank lending companies that leverage P2P lending platforms achieve greater portfolio growth and higher return on equity (ROE) compared to those utilizing alternative capital attraction methods. This hypothesis is grounded in the evidence that P2P platforms provide non-bank lenders with access to scalable, cost-effective funding sources and technological efficiencies that enhance their ability to expand loan portfolios and improve financial performance. By testing this hypothesis, our study aims to address the literature gap regarding the impact of innovative financing strategies, such as P2P platforms, on the performance of non-bank lenders, offering new insights into their role in the financial ecosystem.

3. Methodology

3.1. Data Collection

To construct a robust and comprehensive dataset that facilitated the application of our chosen methodology, we aggregated data from multiple reliable sources and compiled it into a unified dataset. Given the nature of our analysis, the dataset predominantly consists of annual data, ensuring consistency and comparability over time.

The primary foundation for this dataset came from the Consumer Rights Protection Centre (PTAC) in Latvia, the Estonian Financial Inspection Office, and the National Bank of Lithuania. These institutions maintain up-to-date registries of all non-bank lending companies authorized to operate within their respective jurisdictions. This registry served as the starting point for identifying the full scope of companies within our target sector.

Our sample specifically focused on non-bank consumer loan companies that held or have held consumer loan licenses in one or more Baltic states—Latvia, Lithuania, and Estonia—ensuring that the entities' activities occurred within the expected region and that their loan portfolios consisted of a defined geographic market. The 2024 PTAC list of licensed non-bank lenders, along with equivalent lists from Estonia and Lithuania, were meticulously cross-referenced and verified for accuracy to ensure that no key players were excluded from the analysis.

To construct our dataset, we executed the following steps:

1. **Identifying Non-Bank Consumer Loan Providers:** We gathered legal entity names of all non-bank consumer loan providers and identified whether they currently had an active license. For Latvia, this information was retrieved from the Consumer Rights Protection Centre (PTAC), for Estonia from the Estonian Financial Inspection Office, and for Lithuania from the National Bank of Lithuania. For Latvia and Estonia, companies that were out of business were also extracted, but Lithuania's database did not display such companies.
2. **Determining Bank Affiliation:** We investigated whether these entities were related to banks, as this would indicate access to cheaper funding for business

ventures. For Estonian companies, this information was directly available in the Financial Inspection Office database. For Latvian and Lithuanian companies, shareholder data was examined to determine whether an entity with a banking license held shares in a given company. If such a link existed, the company was classified as bank-related, indicating exposure to the advantages of cheaper funding.

3. **Identifying P2P Platform Listings:** We compiled information on whether companies were listed on peer-to-peer (P2P) lending platforms and determined the year of listing. We checked all known P2P lending platforms, including TWINO, Mintos, Debitum, ViaInvest, Swaper, Income Marketplace, Scramble, IUVO Group, Monestro, Brickfy, Nibble, Moncera, SaveLend, Bondster, Robocash, PeerBerry, Hive5, Credon, Afranga, Kviku Finance, Lendermarket, Invers, Circulantis, Roger, Dbitos, Edebex, and Inversa. If a company was listed, it was usually found under the section "Loan Originators" or "Loan Companies," along with the year it joined the respective platform. If a specific year was not found, the incorporation date on the respective platform was verified using media and blog articles. To double-check whether any company was listed on other platforms or had been delisted, additional searches were conducted using AI-powered tools such as ChatGPT and Perplexity AI to find references to such occurrences.
4. **Extracting Financial Data:** We retrieved financial data of these companies from Orbis. We extracted key financial metrics such as Total Assets, Shareholders' Equity, and Net Profit for further analysis.

The final dataset encompasses approximately 180 non-bank lending companies operating across the Baltic states during the period 2014-2022. The control group comprises 160 non-bank lenders who never adopted P2P lending during the observation period, while the treatment group consists of approximately 20 P2P lending adopters who integrated peer-to-peer lending platforms into their funding strategies at various points during the study period. This composition reflects the actual market dynamics in the Baltic states and creates a natural experimental design for analyzing the impact of P2P lending adoption on financial performance within the regional non-bank lending sector.

3.2. Research Methodology

The goal of this study is to understand the effects on non-bank lender growth and profitability through capital attraction tools, specifically peer-to-peer (P2P) financing. As such authors employ a unified and robust methodology to understand the effects of adapting P2P financing.

To quantify the effects of P2P financing adaptation, the authors chose the Difference in Differences (DiD) methodology. The use of this methodology allows authors to observe the effect of treatment, in this case, the adaptation of P2P financing for non-bank lenders. However, given that P2P financing is adapted during different periods across different companies, authors will use a modified DiD methodology proposed by Callaway and Sant'Anna (2020), to account for the time difference between treatments.

Although one might argue that such a methodology is unnecessary given that this could be approached by using Two Way Fixed Effect (TWFE) regression, there has been some recent literature highlighting problems with this approach. First of all, based on the model itself, TWFE assumes that the treatment effect is equal across all units and at all times (Borusyak, Jaravel, & Spiess, 2024). One non-bank lender could be more technology savvy and in turn, utilize P2P lending better, some lending companies differ in their offering and could have better synergies with P2P lending, and so on. This is to say that in our case, it is highly likely that the effects of receiving treatment for different companies are heterogeneous in nature. Using TWFE regression in such a case could lead to misleading results as these heterogeneous effects could contaminate next-period effects, giving rise to pre-treatment trends for a given period (Sun & Abraham, 2021). As such we decided to follow the methodology that addresses these additional factors.

Following the methodology, the authors define a new variable, containing the first period when each company becomes treated. To achieve this, we use data collected and described in our Data section. If the company is never treated, we set the variable to 0, which allows us to define this subsection as our control group.

Based on paper by Marcus and Sant'Anna exploring the differences between different parallel trend assumptions in DiD regressions designs (2021), we opt to define a fixed control group, instead of using a dynamic one, given that we have a large quantity of observed never-treated companies. We believe that this approach suits our research problem better since the adoption of P2P financing has been spread out over almost a decade. In such a case it is reasonable to assume that not only the economic situation has changed but also the regulation surrounding the non-banking sector. With less stringent regulation, companies that were at the forefront of adopting P2P financing could have leveraged it more than those of today. As such, based on the same paper, we define our parallel trends assumption related to never treated units, which is as follows:

$$\mathbb{E}[Y(0)_t - Y(0)_{t-1} | Treated, X] = \mathbb{E}[Y(0)_t - Y(0)_{t-1} | Control, X]$$

Where:

$Y(0)_t -$ the potential outcome at time *t* if *Y* never participates in the treatment

$Y(0)_{t-1} -$ the potential outcome for *Y* at time *t-1* if *Y* never participates in the treatment

$X -$ a vector of all control variables

$Treated -$ an indicator showing that *Y* has been treated at some period

$Control -$ an indicator showing that *Y* is a part of control group

In other words, this assumption states that before treatment, the expected change in outcomes should be equal for both treated and control groups, conditional on covariates X, meaning that if there was no treatment, both groups would have continued on parallel paths.

Additionally, we assume that once a company adopts P2P financing, it continues to use these platforms for the following periods. As far as we are aware, no company has stopped using P2P financing completely in our sample. There have been instances where companies switch to different P2P platforms, but that does not imply that treatment has ended, thus rendering this condition as met.

Given that our sample includes a high number of companies not participating in the treatment, we wanted to include extra robustness checks, and as such we are using Doubly Robust Estimation in our model. Thus, for our results, we do not have to solely rely on running regressions as we are including propensity score matching for a better fit between control and treatment groups. The specific details on how this propensity score is defined can be found in Callaway et al. (2020) paper but in basic terms it weighs each company's chances to adapt P2P lending in certain period based on our control variables and on companies' affiliation with being in control or treated groups. Using these propensity scores, we can find a better fit between treated and control companies with similar scores, ensuring that the end estimation is more robust.

To have a better match for propensity scores and to account for certain pre-treatment trends in our model, we propose certain control variables. Given our model and the sector in general, we are limited by certain data requirements and availability. From the model standpoint, to allow for different adaptation times, these control variables should be time-invariant in nature, meaning that they are constant throughout the years. A good example in this case is each company's founding data, it is fixed and does not change as years go by. If we look from the sector standpoint, some data is hard to come by, certain metrics that describe loans, such as average loan amount, loans issues and so on, are often kept secret. Of course, some data can be collected form P2P platforms, but that does not help when looking at companies not using P2P financing. Additionally, one could look at annual reports to gather some insights, but this approach has its flaws, the biggest one being that there are no certain standards on how issued loans should be reported. By this we mean that each company reports these loans in their own lines, which complicates the data extraction process, especially when faced with a substantial number of companies. Given these restrictions, we propose the following variables: total assets, relation to banks, founding date and country of operations.

To account for differences in growth and profitability, firm size is an important measure. Larger companies usually are more stable and thus might grow slower, while the opposite is often true for small companies. Whatever the effect might be for this sector, we want to account for it. When looking at relevant literature for close fields, such as banking, few notable proxies emerge. Paper by Schildbach (2017), lists these as revenues, total assets, equity capital, market capitalization and other less important proxies. For our case we opt to use total assets, deeming it as most reliable. Even though paper lists revenues as single best proxy, once again due to each company reporting differently, it is not feasible as a measure. Not only is information regarding total assets relatively easy to gather but also this measure is used by researchers most frequently.

We opt to include a dummy variable, indicating relation to banks. This distinction is particularly important when considering ways companies can attract capital. In the case when relation with bank is found, these companies, often subsidiaries for banks, enjoy "cheaper money" than non-bank associated lenders. In such cases, it is highly unlikely that these companies would themselves use P2P financing, when getting a loan from their mother bank for low interest rates is on the table.

The founding date and country of operations provide additional contextual controls that may influence P2P adoption decisions. The founding date helps account for potential technological readiness and organizational flexibility, as newer companies might be more inclined to adopt innovative financing solutions. The country of operations, defined as the jurisdiction where the company holds its primary lending license, accounts for different regulatory environments across the Baltic states. This is particularly relevant as Estonia, Latvia, and Lithuania, while similar in many aspects, maintain distinct regulatory frameworks for non-bank lenders.

Our analysis employs two distinct dependent variables (Y) to capture different aspects of non-bank lender performance following P2P financing adoption. First, we measure growth through year-over-year (YoY) change in balance sheet size, calculated as:

$$YoY\_Change_{i,t} = \frac{Total\_Assets_{i,t} - Total\_Assets_{i,t-1}}{Total\_Assets_{i,t-1}}$$

This metric allows us to capture the expansion or contraction of lending activities, as total assets primarily consist of issued loans in non-bank lending institutions. Secondly, we examine profitability through Return on Equity (ROE), defined as:

$$ROE_{i,t} \; = \; Net\_Income_{i,t} / \; \frac{Equity_{i,t} + Equity_{i,t-1}}{2}$$

ROE serves as an appropriate measure of profitability as it accounts for the efficiency with which companies utilize their initial investment to generate earnings, particularly relevant in the lending sector.

These two dependent variables allow us to examine both the growth dynamics and operational efficiency impacts of P2P financing adoption. By running separate regressions for each dependent variable while maintaining the same specification structure, we can identify whether P2P financing adoption affects growth and profitability differently, providing a more nuanced understanding of its impact on non-bank lenders.

While our methodology differs from standard DiD in its treatment of timing, the underlying process remains consistent with traditional DiD analysis. For each adoption period, we estimate separate treatment effects, allowing us to capture potential heterogeneity in the impact of P2P financing adoption across different time periods. As such, we propose the following basic regression equation:

$$Y_{i,t} = \beta_1 D_i^{Treated} + \beta_2 D_t^{Post} + \beta_3 \left(D_i^{Treated} D_t^{Post}\right) + \beta_4 Total\_Assets_{i,t} + \beta_5 D_i^{Bank} + \beta_6 fdate_i + \beta_7 country_i + \varepsilon_{i,t}$$

Where:

$Y_{i,t}$ – represents our outcome variables (growth and profitability metrics) for company *i* at time *t*

$D_i^{Treated}$ – a dummy variable indicating whether company *i* ever adopts P2P financing

D_t^{Post} – a dummy variable that indicates the post-treatment period

$D_i^{Treated} D_t^{Post}$ – interaction term capturing the treatment effect

$Total\_Assets_{i,t}$ – represents total assets for each firm

D_i^{Bank} – indicates whether the company is a subsidiary of a bank

$fdate_i$ – represents the founding date

$country_i$ – represents the country of operations

$\varepsilon_{i,t}$ – the error term

The key parameter of interest in our analysis is the Average Treatment Effect on the Treated (ATT), which we calculate for each group g (defined by adoption timing) and time period t:

$$ATT(g,t) = \mathbb{E}[Y_t - Y_{g-1} | Treated] - \mathbb{E}[Y_t - Y_{g-1} | Control]$$

Where:

Y_t – the observed outcome at time

Y_{g-1} – the observed outcome for *Y* at time *g-1*, where g indicates the the time period where the treatment is first adapted

$Treated$ – an indicator showing that *Y* has been treated at some period

$Control$ – an indicator showing that *Y* is a part of the control group

This specification allows us to estimate the causal effect of P2P financing adoption while accounting for the staggered nature of adoption across different companies and time periods. The ATT provides insights into how P2P financing adoption affects company performance relative to what would have happened in the absence of adoption, considering both the timing of adoption and the characteristics of different adopter groups.

4. Analysis and Discussion of Results

This section aims to provide an overview of the results in accordance with the developed methodology. Additionally, the authors will discuss the obtained results, possible limitations, and overall implications.

4.1. Return on Equity

Performing the aforementioned methodology yields statistically insignificant results for most groups (p-value < 0.5). As seen in Figure 4, an excerpt from the full regression output in Appendix A, only two years of P2P adoption show signs of significance: 2019 and 2021.

```
Group-Time Average Treatment Effects:
 Group Time ATT(g,t) Std. Error [95% Simult.  Conf. Band]

  2019 2015       NA         NA           NA          NA
  2019 2016       NA         NA           NA          NA
  2019 2017   0.2644     0.0976      -0.0045      0.5334
  2019 2018  -0.2382     0.0836      -0.4684     -0.0080 *
  2019 2019   0.0442     0.0586      -0.1173      0.2056
  2019 2020   0.2603     0.2695      -0.4821      1.0027
  2019 2021   0.8805     0.4526      -0.3662      2.1273
  2019 2022   0.5540     0.0762       0.3440      0.7640 *

  2021 2015       NA         NA           NA          NA
  2021 2016       NA         NA           NA          NA
  2021 2017       NA         NA           NA          NA
  2021 2018       NA         NA           NA          NA
  2021 2019  -0.2363     0.0592      -0.3993     -0.0733 *
  2021 2020  -0.7911     0.0784      -1.0070     -0.5752 *
  2021 2021  -1.7888     0.0552      -1.9409     -1.6367 *
  2021 2022   1.0874     0.0703       0.8938      1.2810 *
---
Signif. codes: `*' confidence band does not cover 0

Control Group:  Never Treated,  Anticipation Periods:  0
Estimation Method:  Doubly Robust
```

Figure 4. Excerpt from regression showcasing Group-Time Average Treatment Effects for ROE. Created by the authors.

According to the regression, non-bank creditors that adopted P2P financing in 2021 experienced a 179% ROE decline in the same year, while in 2022, these firms saw an average 109% ROE growth. For clarity, a graph depicting each group is provided in Appendix A. Although regression lacks statistical significance for certain groups, the graphical results suggest ROE growth for groups such as 2016, 2017, and 2019 when observing average values (the dot marks the average value, and the line represents the 95% confidence band).

Additionally, pre-treatment parallel trends appear valid, as ROE growth effects remain near zero for all groups before adoption.

```
Overall summary of ATT's based on event-study/dynamic aggregation:
    ATT     Std. Error     [ 95%  Conf. Int.]
 0.0312         0.0637    -0.0937       0.1562
```

Figure 5. Regression showcasing the Overall summary of ATT's based on event-study aggregation for ROE. Created by the authors.

When aggregating ATT results dynamically across all groups, no statistically significant results emerge, as shown in Figure 5. The full regression output for this event-study aggregation is in Appendix A. For further clarity, Figure 6 illustrates the average effect by length of exposure. The zero point represents the P2P adoption year, while other values on the X-axis denote years relative to adoption.

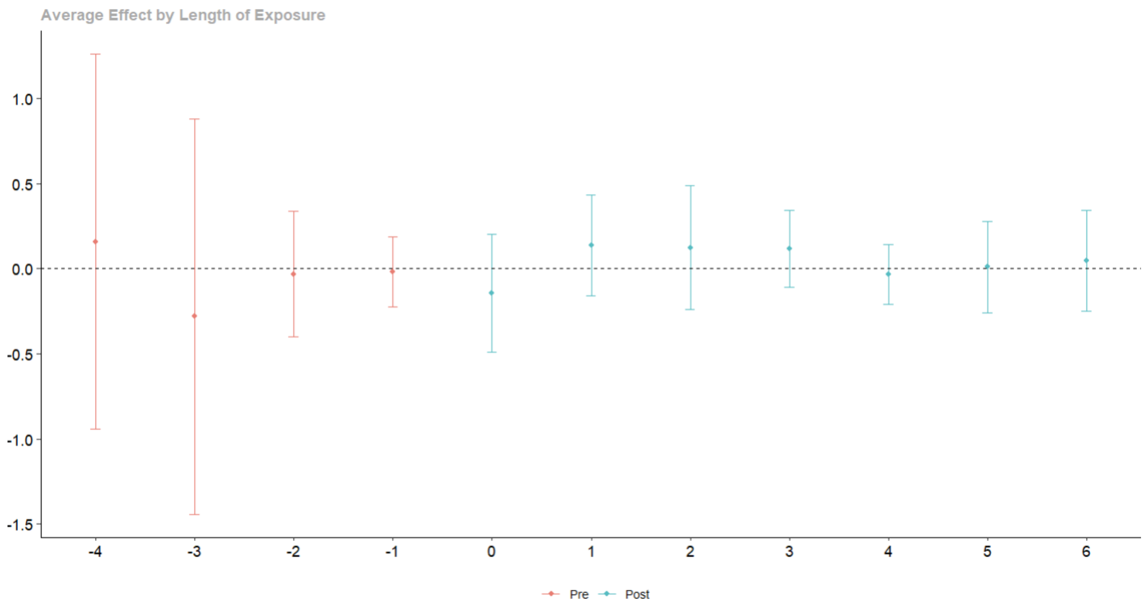

Figure 6. Average Effect by Length of Exposure for ROE. Created by the authors.

Though statistically insignificant (the 95% confidence band covers zero for all periods), Figure 6 reveals a potential trend: ROE turns negative in the adoption year but becomes positive for the next three years compared to non-bank lenders using other financing methods.

Interpreting the dip at period 0 is complicated by yearly data granularity—since P2P adoption could occur at any point within a year, underlying trends or noise may affect pre-adoption profitability. Theoretically, this dip could reflect short-term integration costs preceding efficiency gains (Williamson, 1981). Listing and other costs associated with accessing P2P platforms might reduce profitability in the adoption year.

Figure 6 supports this interpretation, showing positive average effects post-adoption, likely due to efficiency gains. However, the positive trend diminishes after three years, possibly due to P2P refinancing offering only medium-term gains; however, due to data limitations, this might not be the case.

```
Overall summary of ATT's based on group/cohort aggregation:
    ATT    Std. Error     [ 95%  Conf. Int.]
 0.0446        0.0602    -0.0734      0.1627


Group Effects:
 Group Estimate Std. Error [95% Simult.  Conf. Band]
  2016  -0.0189     0.0979       -0.2479      0.2101
  2017  -0.0123     0.0542       -0.1390      0.1145
  2018  -0.1717     0.0842       -0.3685      0.0251
  2019   0.4347     0.0592        0.2964      0.5731 *
  2020   0.0652     0.1516       -0.2894      0.4198
  2021  -0.3507     0.0510       -0.4701     -0.2314 *
---
Signif. codes: `*' confidence band does not cover 0

Control Group:  Never Treated,  Anticipation Periods:  0
Estimation Method:  Doubly Robust
```

Figure 7. Regression showcasing the Overall summary of ATT's based on group aggregation and Group Effects themselves for ROE. Created by the authors.

A deeper analysis of specific groups via group-specific aggregation (Figure 7) reveals contrasting outcomes for 2019 and 2021. The 2019 cohort shows a 43% ROE growth, while the 2021 cohort shows a -35% ROE decline compared to the control group. Though insignificant, the aggregated ATT is positive, suggesting a potential treatment effect.

Figure 8 alone could be misleading, as it highlights the 2021 cohort's negative effect without contextualizing it against Figure 6's dip-and-jump pattern. The pronounced dip for 2021 adopters may reflect post-pandemic economic downturns and high-interest-rate environments. While other groups (e.g., early cohorts such as 2016–2018) might theoretically lack benefits due to first-mover disadvantages or insufficient expertise in adopting new funding methods, we believe the most plausible explanation lies in data limitations for firms operating in those years.

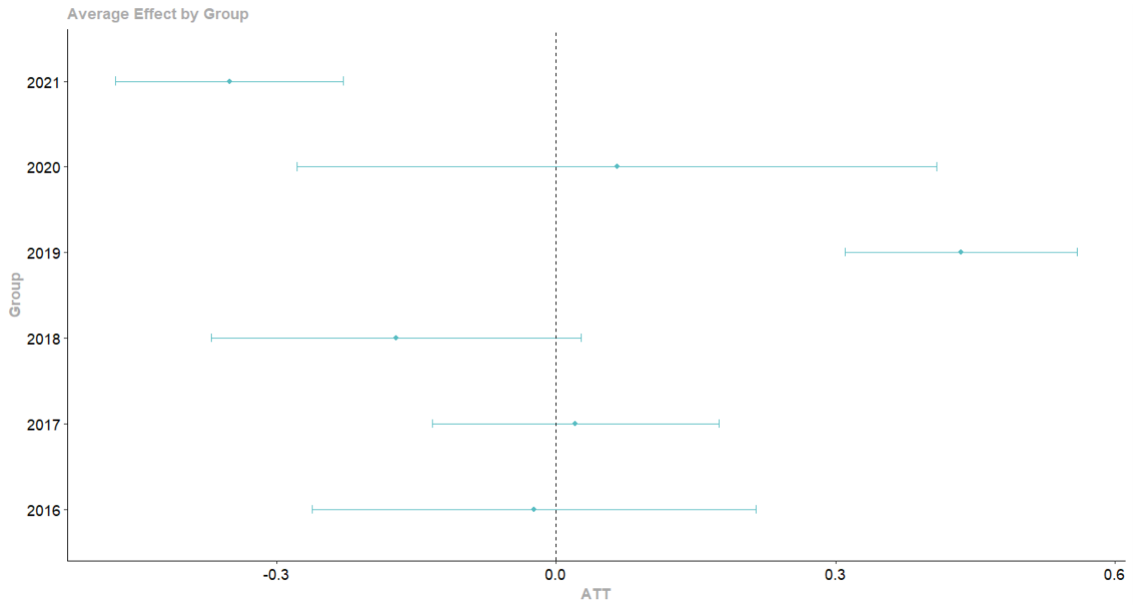

Figure 8. Average Effect by Group for ROE. Created by the authors

4.2. Year-over-Year Change in Total Assets

The analysis of year-over-year (YoY) portfolio growth, measured as the annual percentage change in total assets, reveals distinct patterns compared to ROE outcomes. While the methodological framework remains consistent with the staggered DiD approach, the focus here is on how P2P adoption influences portfolio expansion rather than profitability.

```
Group-Time Average Treatment Effects:
 Group Time ATT(g,t) Std. Error [95% Simult.  Conf. Band]
  2017 2015       NA         NA          NA          NA
  2017 2016   0.1234     0.2891     -0.6039      0.8506
  2017 2017   2.0267     0.1063      1.7592      2.2942 *
  2017 2018   0.3977     0.2146     -0.1421      0.9376
  2017 2019   0.4920     0.0945      0.2542      0.7297 *
  2017 2020   0.1789     0.0987     -0.0693      0.4271
  2017 2021  -0.0841     0.1734     -0.5204      0.3522
  2017 2022   0.1520     0.2749     -0.5395      0.8435
  2018 2015       NA         NA          NA          NA
  2018 2016   0.1783     0.2825     -0.5325      0.8891
  2018 2017   0.0346     0.0570     -0.1087      0.1778
  2018 2018   0.1981     0.0586      0.0507      0.3454 *
  2018 2019   0.2977     0.0684      0.1256      0.4697 *
  2018 2020   0.2564     0.0582      0.1099      0.4028 *
  2018 2021  -0.0642     0.1703     -0.4926      0.3643
  2018 2022  -0.0661     0.1554     -0.4569      0.3248
---
Signif. codes: `*' confidence band does not cover 0

Control Group:  Never Treated,  Anticipation Periods:  0
Estimation Method:  Doubly Robust
```

Figure 9. Excerpt from regression showcasing Group-Time Average Treatment Effects for YoY Total Asset Change. Created by the authors.

Contrary to ROE results, YoY growth shows statistically significant effects for the 2017 and 2018 cohorts, as seen in Figure 9. Firms adopting P2P financing in 2018 experienced 20% portfolio growth in the adoption year, followed by 30% and 26% growth in subsequent years. The 2017 cohort saw an exceptional 229% expansion in the adoption year, declining to 49% growth two years later. This disparity may stem from differences in company behaviour: 2017 adopters likely pursued aggressive portfolio expansion via P2P platforms, though data limitations (discussed in a later section) prevent definitive conclusions.

```
Overall summary of ATT's based on event-study/dynamic aggregation:
   ATT    Std. Error     [ 95%  Conf. Int.]
  0.79        0.3118      0.179      1.4011 *


Dynamic Effects:
 Event time Estimate Std. Error [95% Simult.  Conf. Band]
         -4   0.3889     0.3107        -0.3203      1.0981
         -3   0.7339     0.2946         0.0615      1.4063 *
         -2  -2.2475     2.6105        -8.2057      3.7107
         -1  -0.2889     0.3848        -1.1672      0.5895
          0   0.4636     0.1962         0.0158      0.9113 *
          1   1.1476     1.0272        -1.1969      3.4921
          2   1.2966     1.1859        -1.4102      4.0033
          3   1.9053     1.9015        -2.4348      6.2454
          4   0.2091     0.1550        -0.1447      0.5630
          5   0.1543     0.2241        -0.3571      0.6658
          6   0.3537     0.3812        -0.5164      1.2239
---
Signif. codes: `*' confidence band does not cover 0

Control Group:  Never Treated,  Anticipation Periods:  0
Estimation Method:  Doubly Robust
```

Figure 10. Regression showcasing the overall summary of ATT's based on event-study aggregation for YoY Growth. Created by the authors.

Aggregating ATT results dynamically across all periods yields a statistically significant 79% average portfolio growth for P2P adopters compared to non-adopters (Figure 10). A closer examination of dynamic effects reveals that adopters achieved 46% growth in the adoption year alone, likely due to immediate access to P2P platforms for loan listings. Unlike ROE, which reflects delayed profitability adjustments, YoY growth captures instantaneous portfolio scaling. While later periods show statistically insignificant growth, it is higher than in the first period, possibly reflecting firms gaining expertise in P2P operations over time.

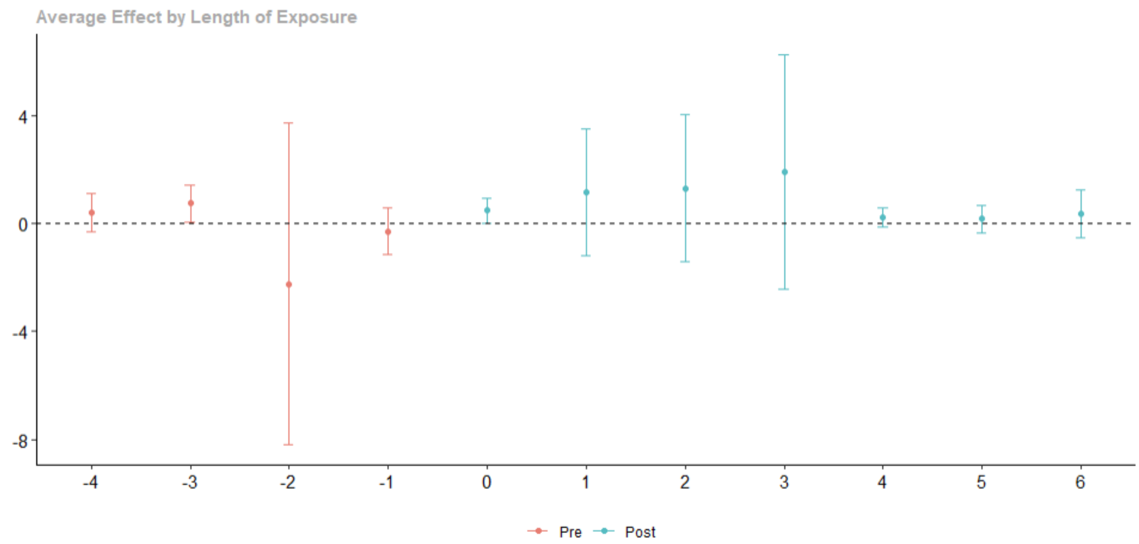

Figure 11. Average Effect by Length of Exposure for YoY Growth. Created by the authors.

Pre-treatment parallel trends appear valid one year prior to adoption (Figure 11), though earlier periods show noise from unobserved factors. Graphically, YoY growth slows and fiddles out after year 3, mirroring ROE trends but without an initial dip. This stagnation after year 3 may reflect firms transitioning to cheaper funding sources (e.g., bonds, IPOs, partnerships with banks) as they mature, reducing reliance on P2P platforms.

When aggregating via the group aggregation method, authors observe statistically significant results as well. In this case, the regression shown in Figure 12 showcases that non-bank lenders who adopted P2P lending experienced 98% portfolio growth compared to other financing methods.

```
Overall summary of ATT's based on group/cohort aggregation:
    ATT     Std. Error     [ 95%  Conf. Int.]
 0.9752         0.1557       0.67       1.2803 *


Group Effects:
 Group Estimate Std. Error [95% Simult.  Conf. Band]
  2016   0.4518     0.2874        -0.1920      1.0957
  2017   0.5272     0.1491         0.1933      0.8611 *
  2018   0.1244     0.0645        -0.0200      0.2688
  2019   4.3967     0.8443         2.5056      6.2879 *
  2020  -0.0674     0.0962        -0.2828      0.1481
  2021   0.0196     0.1113        -0.2296      0.2688
---
Signif. codes: `*' confidence band does not cover 0

Control Group:  Never Treated,  Anticipation Periods:  0
Estimation Method:  Doubly Robust
```

Figure 12. Regression showcasing the overall summary of ATT's based on group aggregation for YoY Growth. Created by the authors.

The real effect, however, might be closer to 50% portfolio growth since the 2019 group is inflating the value of ATT. Although data was filtered to exclude the top and bottom 1% values, to account for extreme cases, the 2019 group could just consist of a few companies that expanded heavily through P2P platforms, given that we observed a similar spike with ROE.

The extreme effect is evident in Figure 13, which highlights the disproportionately high impact for the 2019 cohort. The graph also indicates that older groups maintained a positive trend in portfolio expansion until 2020. This shift could be attributed to the introduction of new regulations, which increased entry barriers and subsequently reduced participation in the treatment.

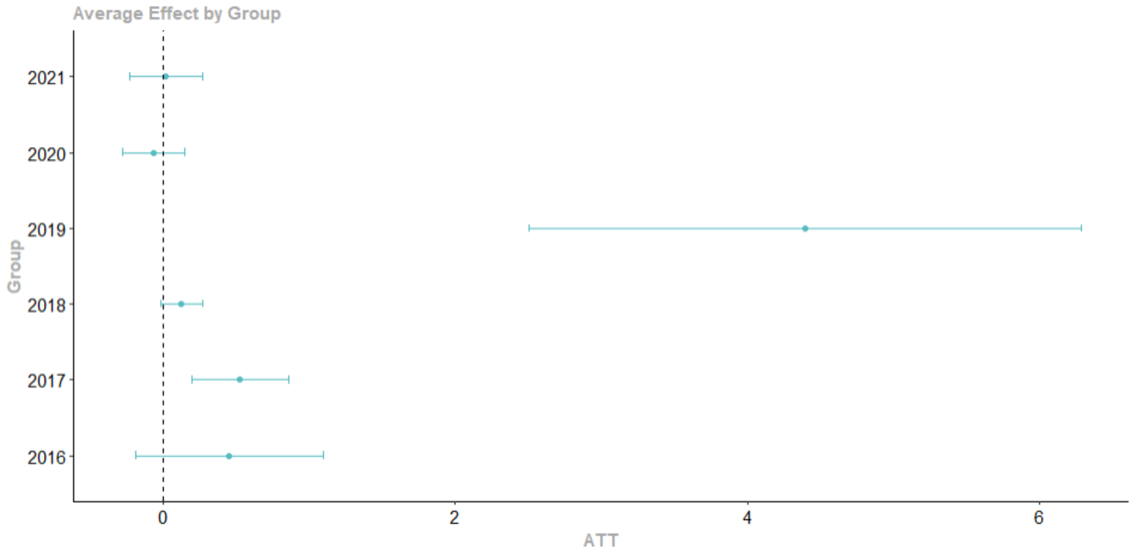

Figure 13. Average Effect by Group for YoY Growth. Created by the authors.

4.3. Limitations

By far, the biggest limiting factor of this study is the small sample size, which restricts the full utilization of our methodology for drawing robust conclusions. The issue stems from the fact that only a handful of P2P adoptions occur in this region annually, and expanding the scope to a broader geographic area could undermine the research goal itself, which is understanding the underlying factors of Baltic non-bank lenders' success.

The limited sample size complicates the incorporation of covariates into the model, as adding controls risks overfitting or producing unreliable estimates due to insufficient observations. This constraint reduces the precision of our estimates and weakens our ability to detect statistically significant effects. Nonetheless, we can still observe trends and some statistically significant outcomes, though these results may contain noise that must be considered during interpretation.

From a data-availability perspective, platform limitations introduce potential biases. P2P platforms do not display delisted companies unless they are reported by external news sources, leading to their omission from the dataset. This creates survivorship bias, as failed firms are likely underrepresented. Additionally, the sample could have been expanded with access to a comprehensive list of defunct Lithuanian companies. The absence of such data narrows the scope and may compromise the accuracy of conclusions.

Methodologically, beyond the sample size limitations, two key areas of concern arise: parallel trends assumption and covariate variation. Our model assumes time-invariant covariates, meaning control variables that change over time are fixed at their baseline values. While necessary for our approach, this simplification risks bias if critical covariates (e.g., firm size) exhibit significant temporal variation. Regarding the parallel trends' assumption, while reasonable for our context, it is not particularly strong due to the small number of observations. With a larger dataset, we could more rigorously assess pre-treatment trends and validate the assumption more confidently.

Despite these limitations, the study provides valuable insights into non-bank lenders' P2P adoption patterns. Future research, however, would benefit from larger datasets and enhanced data tracking to ensure more comprehensive and statistically reliable analyses.

5. Conclusion

This study set out to test the hypothesis that *companies leveraging P2P lending platforms achieve greater portfolio growth and higher return on equity (ROE) compared to those utilizing other capital attraction methods*. While the results broadly support this hypothesis, they should be taken as a direction of trends rather than precise numbers, such as 79% portfolio growth, due to sample size limitations.

Nonetheless, the findings demonstrate a statistically significant association between P2P financing and increased portfolio growth, measured by year-over-year changes in Total Assets. Although not as statistically strong as portfolio growth, ROE growth also showed signs of positive effect from P2P adoption. As such, companies that adopted P2P financing saw, on average, 79-98% portfolio growth compared to other capital-raising methods.

Our research highlights an important aspect not mentioned in previous studies: non-bank lenders adopting P2P platforms experienced reduced profitability in the treatment year, likely due to integration and compliance costs. This effect diminishes a year after initial treatment, showcasing that profitability bounces back as the loans listed on P2P platforms bring in new revenue. In contrast, portfolio growth showed immediate positive effects, as integration costs did not affect Total Asset accumulation.

Additionally, the observed benefits for both profitability and portfolio growth diminished after three years. While sample size constraints may partially explain this trend, we believe that this is caused by firms transitioning to lower-cost financing options (e.g., bond issuance, IPOs, or bank partnerships) as they mature.

These findings suggest that P2P financing is a viable and impactful strategy for non-bank lenders pursuing rapid growth, particularly in digitally advanced markets like the Baltics. However, the profitability outcomes depend on timing, execution, and market context, meaning that firms must approach P2P adoption with a well-considered operational strategy.

This study contributes to a relatively under-researched area by focusing on the Baltic region—an emerging market for fintech lending—and by offering empirical evidence on the effectiveness of P2P-based capital strategies, measured by profitability and portfolio growth.

Ultimately, this thesis offers valuable insights for policymakers, industry practitioners, and academic researchers interested in the evolving role of fintech in reshaping access to credit and the structure of modern financial markets.

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Google folder with full-text materials:

https://drive.google.com/drive/folders/12sEI1Dmz-zo-nB_-PVbZfv8LJKJteDBl?usp=sharing

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7. Appendices

Appendix A. Staggered DID Regression results and their corresponding graphs for ROE

Figure 1. Group-Time Regression Output for ROE. Created by the authors.

```
Group-Time Average Treatment Effects:
 Group Time ATT(g,t) Std. Error [95% Simult.  Conf. Band]
  2016 2015       NA         NA          NA          NA
  2016 2016  -0.1851     0.1364     -0.5610      0.1907
  2016 2017   0.0835     0.1334     -0.2841      0.4510
  2016 2018  -0.0531     0.0952     -0.3152      0.2090
  2016 2019   0.0434     0.1182     -0.2821      0.3690
  2016 2020   0.0710     0.1342     -0.2988      0.4407
  2016 2021  -0.1397     0.1266     -0.4884      0.2090
  2016 2022   0.0478     0.1187     -0.2792      0.3748
  2017 2015       NA         NA          NA          NA
  2017 2016   0.1659     0.0839     -0.0651      0.3968
  2017 2017   0.1349     0.1019     -0.1458      0.4157
  2017 2018  -0.1727     0.1141     -0.4869      0.1415
  2017 2019  -0.0549     0.0661     -0.2371      0.1273
  2017 2020   0.0058     0.0744     -0.1991      0.2107
  2017 2021  -0.1638     0.0647     -0.3422      0.0145
  2017 2022   0.1770     0.1342     -0.1928      0.5468
  2018 2015       NA         NA          NA          NA
  2018 2016  -0.0648     0.0785     -0.2810      0.1513
  2018 2017   0.1907     0.0976     -0.0782      0.4597
  2018 2018  -0.1846     0.0836     -0.4148      0.0456
  2018 2019  -0.1185     0.1190     -0.4461      0.2092
  2018 2020  -0.1866     0.1011     -0.4649      0.0918
  2018 2021  -0.2689     0.1049     -0.5579      0.0200
  2018 2022  -0.0998     0.0895     -0.3463      0.1466
  2019 2015       NA         NA          NA          NA
  2019 2016       NA         NA          NA          NA
  2019 2017   0.2644     0.0976     -0.0045      0.5334
  2019 2018  -0.2382     0.0836     -0.4684     -0.0080 *
  2019 2019   0.0442     0.0586     -0.1173      0.2056
  2019 2020   0.2603     0.2695     -0.4821      1.0027
  2019 2021   0.8805     0.4526     -0.3662      2.1273
  2019 2022   0.5540     0.0762      0.3440      0.7640 *
  2020 2015       NA         NA          NA          NA
  2020 2016   0.1929     0.4699     -1.1016      1.4873
  2020 2017  -0.3131     0.5245     -1.7578      1.1316
  2020 2018  -0.1950     0.3808     -1.2439      0.8538
  2020 2019   0.1097     0.0577     -0.0491      0.2685
  2020 2020  -0.0088     0.0824     -0.2357      0.2181
  2020 2021   0.2026     0.4389     -1.0065      1.4117
  2020 2022   0.0017     0.1129     -0.3092      0.3126
  2021 2015       NA         NA          NA          NA
  2021 2016       NA         NA          NA          NA
  2021 2017       NA         NA          NA          NA
  2021 2018       NA         NA          NA          NA
  2021 2019  -0.2363     0.0592     -0.3993     -0.0733 *
  2021 2020  -0.7911     0.0784     -1.0070     -0.5752 *
  2021 2021  -1.7888     0.0552     -1.9409     -1.6367 *
  2021 2022   1.0874     0.0703      0.8938      1.2810 *
---
Signif. codes: `*' confidence band does not cover 0
```

Figure 2. Graph showcasing the regression output for each group. Created by the authors.

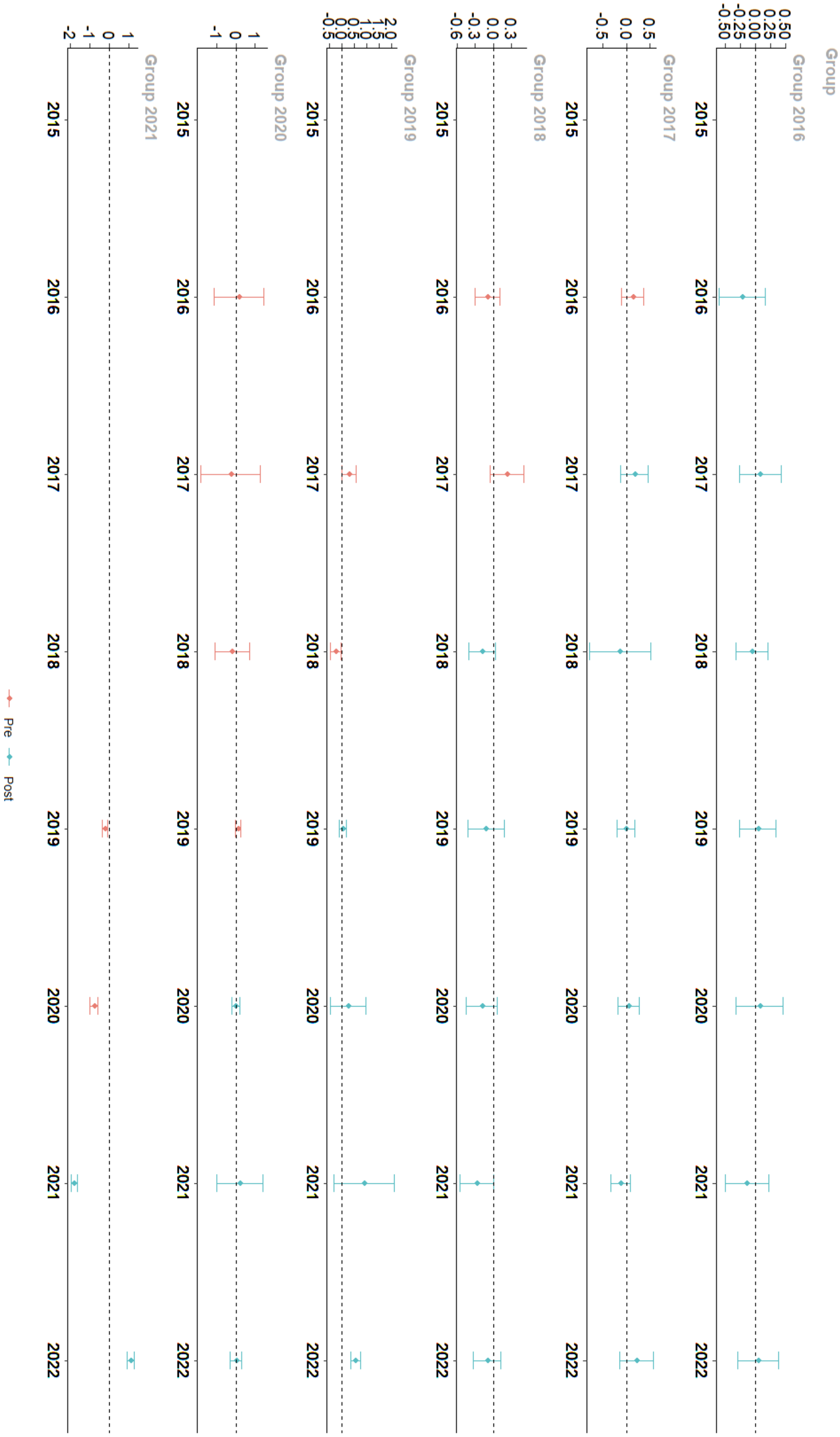

Figure 3. Regression output showcasing Dynamic Effects and Aggregation. Created by the authors.

```
Overall summary of ATT's based on event-study/dynamic aggregation:
    ATT    Std. Error     [ 95%  Conf. Int.]
 0.0312        0.0637    -0.0937      0.1562


Dynamic Effects:
 Event time Estimate Std. Error [95% Simult.  Conf. Band]
         -4   0.1929     0.4630       -0.8972      1.2829
         -3  -0.3131     0.5669       -1.6476      1.0214
         -2  -0.0353     0.1506       -0.3898      0.3193
         -1  -0.0144     0.0863       -0.2176      0.1887
          0  -0.1410     0.1416       -0.4742      0.1923
          1   0.1328     0.1253       -0.1622      0.4278
          2   0.1186     0.1510       -0.2367      0.4740
          3   0.1096     0.0936       -0.1107      0.3300
          4  -0.0453     0.0787       -0.2304      0.1399
          5  -0.0040     0.1165       -0.2781      0.2702
          6   0.0478     0.1240       -0.2441      0.3397
---
Signif. codes: `*' confidence band does not cover 0

Control Group:  Never Treated,  Anticipation Periods:  0
Estimation Method:  Doubly Robust
```

Appendix B. Staggered DID Regression results and their corresponding graphs for YoY Change

Figure 1. Group-Time Regression Output for YoY Change. Created by the authors.

```
Group-Time Average Treatment Effects:
 Group Time ATT(g,t) Std. Error [95% Simult.  Conf. Band]
  2016 2015       NA         NA          NA          NA
  2016 2016   0.2968     0.3297     -0.5324      1.1261
  2016 2017   0.5096     0.2797     -0.1939      1.2131
  2016 2018   0.5157     0.2912     -0.2169      1.2483
  2016 2019   0.7641     0.2761      0.0695      1.4587 *
  2016 2020   0.5666     0.2711     -0.1154      1.2486
  2016 2021   0.1561     0.3170     -0.6414      0.9536
  2016 2022   0.3537     0.3697     -0.5762      1.2837
  2017 2015       NA         NA          NA          NA
  2017 2016   0.1234     0.2891     -0.6039      0.8506
  2017 2017   2.0267     0.1063      1.7592      2.2942 *
  2017 2018   0.3977     0.2146     -0.1421      0.9376
  2017 2019   0.4920     0.0945      0.2542      0.7297 *
  2017 2020   0.1789     0.0987     -0.0693      0.4271
  2017 2021  -0.0841     0.1734     -0.5204      0.3522
  2017 2022   0.1520     0.2749     -0.5395      0.8435
  2018 2015       NA         NA          NA          NA
  2018 2016   0.1783     0.2825     -0.5325      0.8891
  2018 2017   0.0346     0.0570     -0.1087      0.1778
  2018 2018   0.1981     0.0586      0.0507      0.3454 *
  2018 2019   0.2977     0.0684      0.1256      0.4697 *
  2018 2020   0.2564     0.0582      0.1099      0.4028 *
  2018 2021  -0.0642     0.1703     -0.4926      0.3643
  2018 2022  -0.0661     0.1554     -0.4569      0.3248
  2019 2015       NA         NA          NA          NA
  2019 2016       NA         NA          NA          NA
  2019 2017  -0.1724     0.0570     -0.3157     -0.0292 *
  2019 2018   0.0798     0.0586     -0.0676      0.2271
  2019 2019   0.0434     0.0631     -0.1154      0.2022
  2019 2020   5.3038     3.9772     -4.7011     15.3086
  2019 2021   5.7734     4.2049     -4.8042     16.3510
  2019 2022   6.4664     5.4696     -7.2926     20.2254
  2020 2015       NA         NA          NA          NA
  2020 2016   0.3889     0.3155     -0.4047      1.1825
  2020 2017   0.7339     0.2695      0.0559      1.4119 *
  2020 2018  -0.5710     0.3965     -1.5683      0.4263
  2020 2019  -0.2240     0.2226     -0.7841      0.3360
  2020 2020   0.0354     0.1015     -0.2199      0.2907
  2020 2021  -0.0808     0.1805     -0.5347      0.3732
  2020 2022  -0.1566     0.1633     -0.5674      0.2542
  2021 2015       NA         NA          NA          NA
  2021 2016       NA         NA          NA          NA
  2021 2017       NA         NA          NA          NA
  2021 2018       NA         NA          NA          NA
  2021 2019 -20.0302     0.0621    -20.1865    -19.8739 *
  2021 2020  -3.5378     0.0601     -3.6891     -3.3866 *
  2021 2021  -0.0544     0.1579     -0.4515      0.3427
  2021 2022   0.0937     0.1510     -0.2861      0.4734
---
Signif. codes: `*' confidence band does not cover 0

Control Group:  Never Treated,  Anticipation Periods:  0
Estimation Method:  Doubly Robust
```

Figure 2. Graph showcasing the regression output for each group. Created by the authors.