MSc Business Administration
Master Thesis

The Impact of Currency Risk and Loan Originator Creditworthiness on Cross-Border P2P Lending Rates on Mintos

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Abstract

This study investigates the effects of loan originator creditworthiness (proxied by the Mintos risk score) and exchange rate volatility on the interest rates of cross-border peer-to-peer (P2P) loans on Mintos, the largest Euro-denominated P2P lending platform. The paper uses a dataset of 727,812 loans originated in eight countries over the period of 2022 to 2024, to perform a multiple regression. The findings suggest that loan originator creditworthiness has an economically significant negative effect on the expected lending rates on the platform. In addition to this, findings suggest that exchange rate volatility between the lender and borrower country has an economically significant positive effect on the expected lending rates on the platform. Among the several broader factors investigated in the paper, macroeconomic factors explain the majority of the variance in cross-border P2P loan interest rates. Robustness checks—including year-by-year, country-by-country, and median regression analyses—confirm the stability of these relationships. This study contributes to existing literature by further affirming the importance of borrower creditworthiness on the pricing of P2P loans and offering novel empirical evidence on the effect of exchange rate volatility in the pricing of cross-border P2P loan rates.

Keywords: peer-to-peer (P2P) lending, cross-border lending, currency risk, exchange rate volatility, loan originator creditworthiness, interest rate determinants

Contents

1 Introduction

1.1 P2P Loan Market Landscape

Peer-to-peer (P2P) lending is a form of alternative finance that gained market share alongside financial technology innovations following the 2007-2008 financial crisis (Atz and Bholat, 2016). These alternative finance technologies filled the financing void left by the global crisis by enabling individuals to partially fund personal and business loans of their choosing. This effectively replaced financial institutions with digital brokers that mediate this funding activity. The first P2P lending platform, Zopa, emerged in 2005, shortly before the crisis (Chemyakin, 2016). While the crisis was a main driver in the emergence of such platforms, their growth slowed down significantly in nations with high bank concentration (Havrylchyk et al., 2020). In the past decade, such crowdfunding platforms have enjoyed success in regions with less banking services. This has resulted in increased cross-border capital flow from regions such as Europe (Polyzos et al., 2024). In the United States, P2P platform loan issuance has increased following a sharp decline in traditional loan origination to small businesses following 2007 (Basha et al., 2021). P2P lending platforms satisfy the borrowing needs of creditors with lower creditworthiness while opening up an investment opportunity for lenders willing to take on the additional risk.

The sector has grown from \$3.5 billion in 2013 to \$206.1 billion in 2021, and the market for P2P loans is expected to reach approximately half a trillion dollars by 2027 (Polyzos et al., 2024). The landscape of P2P lending platforms is largely segmented on a national or regional level due to differing regulations and legal requirements imposed by the relevant authorities (Bachmann et al., 2011).

Interest rates on P2P lending platforms can either be set using a reverse auction process or a posted-price mechanism. The auction process allows borrowers on platforms to express a maximum interest rate that they are willing to pay, followed by a bidding process where lenders are able to put forward the amount of funding they are willing to give, as well as the minimum interest rate that they demand (Bachmann et al., 2011). The second process, where the loan originator itself sets a predetermined interest rate, works much like traditional lending, where the originator assesses factors such as the borrowers' characteristics to appropriately reflect the level of risk associated with the loan. Posted-price systems have become more prevalent as the industry matures, as investors often were unable to correctly assess risk under the reverse auction regime. A study of P2P loans to African SMEs on *myc4.com* shows that an average return for lenders on the platform hovered around -20%, showing a lack of ability to correctly account for risks such as default (Mild et al., 2015).

1.2 Significance of Cross-Border P2P Lending

Although financial inclusion may be taken for granted in economically advanced countries, 38% of adults worldwide reported not having access to a bank account in 2014 (Demirgüç-Kunt et al., 2017). According to the Federal Deposit Insurance Corporation (FDIC), 18.5% of American households were not fully banked in 2021, meaning that they had no access to traditional forms of credit (FDIC, 2024). These households relied on more predatory non-bank credit such as payday loans and pawn shops. In countries with less banking infrastructure, particularly those targeted by P2P loan platforms, it is fair to assume that this unbanked population with no access to traditional credit is far larger than in the United States.

Financial inclusion, through P2P lending activity, is higher in rural areas in the United States experiencing bank closures (Maskara et al., 2021). This increased activity is also highly dependent on digital inclusion. Digital inclusion is shown to be positively associated with P2P lending activity, with this relationship being more prominent in areas that may be underbanked, such as high minority population areas and areas with less bank credit activity (Jia and Kanagaretnam, 2022). In accordance with the FDIC survey, urban areas see increased P2P lending activity when the density of pawn shops in the area is lower (Maskara et al., 2021). This trend of P2P lending and other financial technology (fintech) innovations filling the hole left by traditional banking following the global financial crisis is also present worldwide (Beck, 2020). However, there is a lack of consensus on whether such fintech innovations are substitutes or complementary to the traditional financial system. Tang (2021) examines residential lending behavior on P2P platforms and by banks to conclude that the fintech platforms substituted bank credit in the mortgage market. However, they also note that banks and P2P platforms are complementary when looking at small loans as borrowers who migrated to P2P platforms from banks applied for loans larger than typical P2P borrowers but smaller than typical bank loans (Tang, 2021).

Cross-border P2P activity allows individuals in underbanked regions to access capital while providing an investment opportunity to international investors. Fintech innovations are often credited with lowering overhead costs for both the borrower and the lender by automating loan pricing and underwriting through the use of algorithms and by removing barriers preventing borrowers from accessing credit through traditional means (Basha et al., 2021). Lenders are, of course, compensated for this higher risk. During the five year period from 2010 to 2015, P2P platforms had achieved much higher returns than those achieved through bank deposits (Milne and Parboteeah, 2016).

1.3 European Market and Mintos

The P2P lending market in Europe is dominated by two players, Mintos and PeerBerry, which are headquartered in Latvia and Croatia, respectively. Table 1 presents characteristics of the five largest P2P lending platforms in Europe by loanbook value (P2P Invest ApS, 2024).

PLATFORM	COUNTRY	MARKET SHARE	TOTAL VOLUME
Mintos	Latvia	52.96%	10.92B EUR
PeerBerry	Croatia	14.01%	2.89B EUR
TWINO	Latvia	5.33%	1.10B EUR
Robocash	Croatia	5.08%	1.05B EUR
Estateguru	Estonia	4.16%	0.86B EUR

Table 1: Euro denominated P2P Lending Platforms by Market Share (P2P Invest ApS, 2024)

All five of the leading P2P lending platforms mentioned in Table 1 opt for a posted-price mechanism and set interest rates based on internal risk models. Commonly, P2P lending platforms are structured in a way that the platform only acts as a middle man between investors and local loan originators that aggregate credit requests from borrowers. Mintos currently features upwards of 50 lending companies from various countries on their platform (AS Mintos Marketplace, 2025). These lending companies are tasked with bundling individual loans for investors to eventually fund on the platform.

To align incentives, several risk measures are enforced by Mintos on these lending companies.

- Mintos Risk Score: 10.0 (low risk) to 1.0 (high risk) score given by Mintos to their lending companies based on four loan aspects:

  - Loan portfolio performance (weight: 40%) : evaluated based on profits generated in the prior two years, as well as the ratio of non-performing loans (NPL) and characteristics of the products such as liquidity

  - Loan servicer efficiency (weight: 25%) : evaluated through reporting quality of the lending companies and their management track record

  - Buyback strength (weight: 25%) : evaluated through the lending company's financial profile as well as management experience and diversification of revenue streams

  - Cooperation structure (weight: 10%) : evaluated based on lending company's legal structure in terms of recoverability of borrower funds

- Investment currency: Lenders on Mintos often lend to loan originators in a currency other than the lending company's local currency, indicating that the lending companies bear a majority of the currency risk

- Buyback obligation: If indicated as so, lending companies are obligated to buyback loans at nominal value plus accrued interest if payments by local borrowers are more than 60 days late

- Skin In The Game: Lending companies are required to keep a portion of the loans they offer Mintos clients on their own books (anywhere from 2% to 15% as of December 2024)

A typical loan listing process on Mintos begins with the lending company bundling loans into something the platform calls notes. This process is visually shown in Figure 1, where loans from individual borrowers are packaged into a note by the lending company, before being posted on Mintos for funding. These notes can be thought of as an instrument similar to collateralized debt obligations (CDOs), where the traded instrument is a portfolio of multiple loans. Lending companies usually focus on similar types of loan purposes and bundle them into notes composed of loans with similar characteristics. Once a note has been created, it is listed on Mintos for funding by users of the platform. Much like a CDO, users are not able to access much information on the underlying loans besides the amount, purpose, and maturity. Depending on the incentive alignment measures, the lending company will have to offer buyback guarantees or hold the note as a portion of their books.

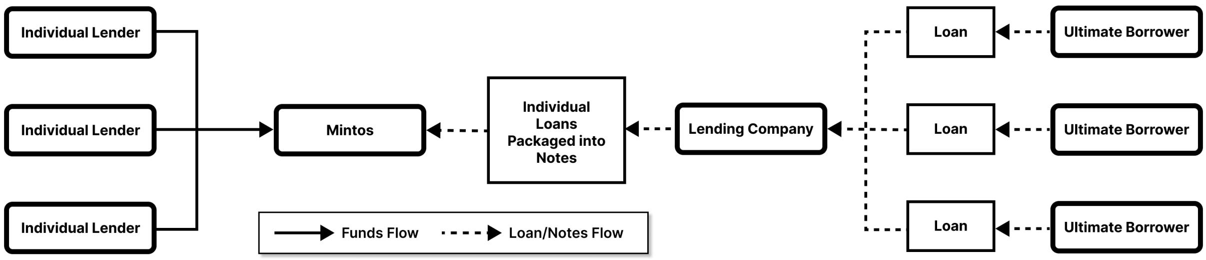


Figure 1: Typical loan/note flow process from ultimate borrower to Mintos

A typical fund flow process is shown visually in Figure 2. When a note has been funded by a user on Mintos, funds are passed on to the lending company, through Mintos, who convert the funds to the appropriate local currency. The lending company is then tasked with distributing funds to individual borrowers. Lending companies receive the principal back in the local currency as well as an interest rate r_1, also in the local currency. Lending companies then repay the Euro loan principal along with an interest rate r_2. As Mintos uses the Euro as their base currency, lending companies have to ensure that the local currency interest they earn from borrowers is sufficiently high to cover the currency risk they bear, ensuring that they are able to return the principal with interest in Euros to Mintos users whilst taking a margin for themselves. Users on Mintos are charged a fee as a percentage of their note holdings. Moving forward, notes and loans will be used interchangeably, but will refer to the financial product that an ultimate lender will see on the Mintos platform. Throughout this paper, a loan's interest rate will refer to the interest rate paid to the lender r_2.

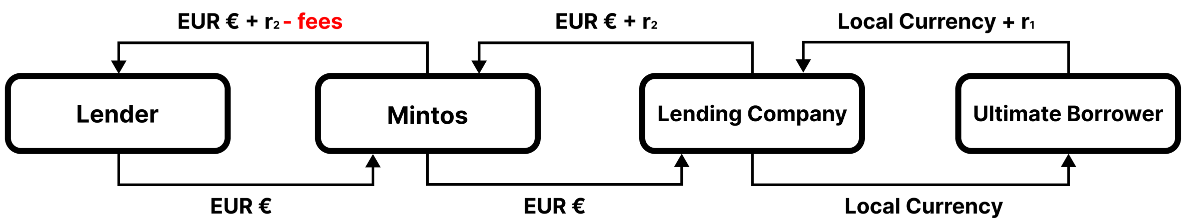


Figure 2: Typical fund flow process from lender to ultimate borrower

1.4 Thesis Statement

Basha et al. (2021) show that only 8% of literature related to P2P lending as of 2021 focus on macroeconomic factors, making the area largely unexplored. On top of this, a review of available literature has shown almost no research into the effects of currency risk on cross-border P2P loans. Although directional research, such as on the effects of currency risk on cross-border flow and foreign direct investment exist, these do not make an explicit connection to how lending rate dynamics change as a result of these risks.

While it may seem, from the investors' perspective, that currency risk is an afterthought due to the inclusion of lending companies and certain guarantees that they offer, the perceived risk may not accurately reflect all factors that would be taken into account under traditional cross-border lending. As P2P lending platforms move from more "personal" lending behavior, where lenders could assess individual loans and their characteristics, to a more obfuscated system where loans are bundled into notes reminiscent of CDOs, more and more trust is passed onto the lending companies for proper risk management. This trust is presented to users of P2P lending platforms in the form of a risk score. *This paper will examine to what extent currency risk and loan originator creditworthiness determines the interest rates of cross-border P2P loans originated on Mintos.*

1.5 Structure

This thesis is organized as follows: Section 2 covers literature on both traditional lending rate determinants and P2P lending rate determinants from a supply-side and demand-side perspective. The findings from this section allow for synthesis of relevant factors in order to develop the hypothesis tests in this paper. Section 3 outlines the research methodology used in this thesis by presenting the data collection process and developing a model. Section 4 covers the empirical results of the study. Section 5 presents the main findings of the research, along with their implications. Finally, Section 6 provides a critical perspective on research limitations while providing key points for future research.

2 Literature Review

2.1 Theoretical Framework

A common issue in P2P lending is the information asymmetry between the lender and the borrowing entity. Although some platforms employ a reverse auction mechanism to combat this asymmetry by providing as much borrower information as possible, it has been shown that lenders are unable to appropriately price the risks involved (Mild et al., 2015). Even when sufficient information was given out to lenders prior to the bidding process, herding behavior from unsophisticated lenders wanting to capture higher returns led to interest rates being bid down to a point where default risk was not appropriately captured. To counter this, a majority of P2P lending platforms switched to a posted-price system where interest rates would be set internally or by loan originators based on sophisticated risk models. Credit or risk scores are used as a signal to give lenders a rough idea of how creditworthy the borrowing entity is. However, incentives between the stakeholders in a P2P loan transaction are not necessarily aligned. The lending process on P2P platforms can be analyzed from the perspective of incentives. The lender's sole incentive is to generate a high return while avoiding borrowers that default. On the other hand, P2P platforms make a majority of their revenue through fees generated on their platforms. As such, they want to maximize loan volumes. Finally, the loan originator wants to maximize their return by capturing the spread in interest charged to the borrower and paid to the lender while avoiding borrower default. When considering the lender and platform relationship in terms of the principal-agent problem, the lender acts as the principal and the P2P platform acts as the agent. The platform is charged with screening loans and assigning a risk score that encapsulates all risk factors associated with the loan originator. However, as the platform relies on fees as their primary revenue source, their incentives are not aligned with lenders. Moral hazards may emerge as a result, where platforms do not accurately compute risk to make loans seem more enticing to lenders. An additional layer of risk exists between the P2P platform and the loan originator as riskier originators may not report their financial health accurately to entice more capital from lenders. Platforms usually combat this by attempting to align the incentives of all players. In the case of Mintos, this is done through the buyback guarantee and by ensuring that a portion of loans are held by the originating entity. However, as buyback guarantees are only valid for a period of time following a loan being funded, loan originators may perceive the trade off of taking on riskier loans as being worth the risk in order to attract more capital. In a highly complex system such as P2P lending, there is a high level of information asymmetry and lack of transparency for the lender.

2.2 Cross-Border Lending

Cross-border lending, which is often seen as a service, rather than a portfolio decision, has been on a downtrend following the 2007-2008 financial crisis (Barrell and Nahhas, 2020). Cross-border capital flows are largely seen as a positive that raises aggregate output but can quickly act as an exporter of risk from home countries to lender countries when financial situations worsen (Barrell and Nahhas, 2020). Cross-border loans to emerging economies often occur in the form of syndicated loans from economically advanced countries. These loans, where multiple financial institutions provide capital to a single borrower under a single loan agreement, gained popularity in the 1970s (Cerutti et al., 2015). Historically, cross-border lending has long followed a boom and bust cycle, ending in contagion that eventually fades to welcome the next craze of cross-border lending (Buchheit, 1995). These boom and bust dynamics are present in most financial activity, where the initial boom is driven by increased economic optimism which eventually crashes as this fades. From a fundamentals perspective, individuals see information that leads to the belief that conditions would improve drastically in the future, which leads to a great downturn when this information is judged to be false (Christiano et al., 2008). The same line of thinking also applies to activity around cross-border lending. Syndicated cross-border loans also experienced severe disruption in the 1980s following elevated defaults in emerging economies, notably Latin America (Cerutti et al., 2015). Buchheit (1995) notes that modern day cross-border lending has shifted from commercial bank loans, as was the case in the 1970s, to international bond markets. The modern day downward trend was preceded by a rapid expansion of cross-border lending, which tripled between 1995 and 2012 to reach $20 trillion, with both syndicated loans and international bonds playing major roles in this international capital flow (Cerutti et al., 2015).

Perceived cross-border capital flow into emerging economies is significantly affected by changes in the monetary policies of economically advanced countries (Makhetha-Kosi et al., 2016). Makhetha-Kosi et al. (2016) highlight that following the United States' decision to begin tapering, where the rate of quantitative easing is reduced, significant capital flowed out of emerging economies. Cross-border loans, as opposed to domestic loans, expose lenders to a multitude of extra risks that must be taken into account. The risk characteristics of the borrower's country greatly influences the ability for lenders to extend cross-border capital (Cerutti et al., 2015). These risks can include aspects such as political risk, currency risk, or legal risks, such as the inability to enforce legal action through foreign legal institutions (Mellor et al., 2024). As such, most cross-border loan deals are denominated in either US dollar, the euro, or the yen and are often priced above the London Inter-Bank Offered Rate (LIBOR) or the prevailing average interest rate (Cerutti et al., 2015). Often times, the euro denominated cross-border loans tend to be more regionally concentrated, as opposed to the US dollar, which experiences less dominance downturn from geographic distances due to its status as the world reserve and trade currency (Emter et al., 2024).

2.3 Interest Rate Determinants in International Lending

Literature on the determinants of interest rates in international lending is scarce. As such, this section will cover both interest rate determinants in domestic lending throughout different countries and the determinants of interest rates in international lending. Trade flows and cross-border bank claims are also fundamentally linked with loan interest rate dynamics. In their working paper for the Bank for International Settlements, Bruno and Shin (2015) look at cross-border banking through the global liquidity lens. As dictated by the international loan supply and demand curve shown in Figure 3, they note that an increase in loan supply, shown by the shifted supply curve $C'_S(r)$, where all else is held equal, forces the equilibrium interest rate downwards. As such, factors that contribute to increased cross-border liquidity and claims, should exert a downwards pressure on loan interest rates as a signal of increased confidence or lower perceived risk. To provide additional context surrounding the determinants of traditional lending rates, determinants of trade flows and bank claims will also be explored.

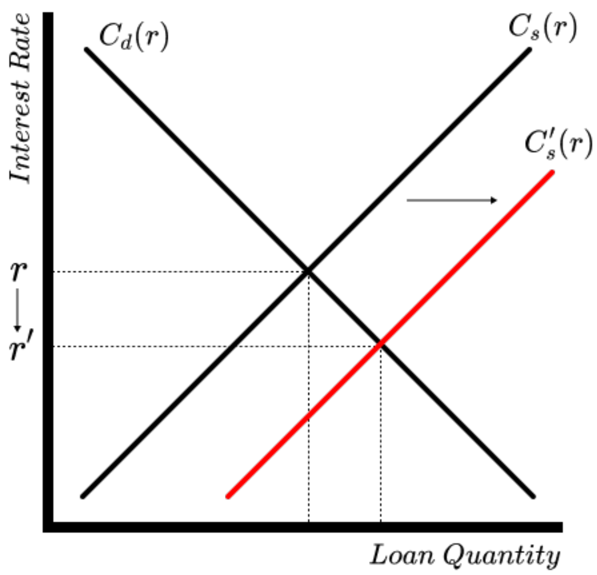


Figure 3: Downward pressure on loan interest rates as a result of aggregate loan supply expansion

The economic cycle greatly affects traditional lending and borrowing activity by banks and other financial institutions. Jeanneau and Micu (2002) highlight that factors affecting lending can be split into push, factors that will encourage lenders to seek borrowers, and pull, factors that will make borrowers more attractive to lenders. For the sake of clarity, these factors will be referred to as supply-side factors, where capital actively seeks borrowers, and demand-side factors, where borrowers attract more capital.

2.3.1 Supply-Side Factors

2.3.1.1 Cost of Capital

As a basic starting point, interest rates must always be linked to the cost of borrowing or cost of capital for the bank or institution, typically the money market rate or treasury bill rate. For short-term loans, these are usually dated between 3 to 5 months and for long-term loans, these are usually dated 1 year (Saunders and Schumacher, 2000). In bank lending in Kenya, market factors, such as credit risk and interbank risk, the cost of funds for banks, including taxes and salaries, as well as inflation, all affect lending rates positively (Kinyuru, 2011). When foreign rates are higher than the domestic cost of capital, a carry trade emerges where domestic financial institutions can collect the spread between the two rates by lending to foreign markets. Odionye et al. (2023) look at the effects of interest rate differentials on capital inflows into Nigeria and determined that a 3.68% differential led to increased investment flow from overseas. They find that if the Nigerian rate is at least 3.68% above the foreign rate, increased cross-border flows can be attributed to it as foreign lenders invest their funds in Nigeria to capture the yield difference (Odionye et al., 2023). Above this threshold, domestic financial institutions in countries such as the US, prefer to lend money in Nigeria to take advantage of the higher lending rates in the country. As these cross-border flows increase, downwards pressure is exerted on the interest rates of the recipient country, bringing down overall rates and reducing the gap between the domestic cost of capital for lenders and the rate they receive overseas. Cerutti et al. (2014) find that interest rate differentials, between lender and borrower countries, are insignificant for non-market based interest rates but significantly negatively related to cross-border bank flows when looking at advanced economies. This is in contrast to much of the literature that mentions the need for increased risk taking when domestic interest rates are low, leading to capital flowing overseas.

2.3.1.2 Risk Appetite

Another major supply-side factor in traditional lending is the risk appetite of the lending entity. Gregor and Melecký (2018) explain risk appetite by looking at the spread between freely traded long-dated government bonds (taken to be the risk free rate) and the policy rate to show how markets reflect risks such as sovereign risks. The widening of this spread signals overall market risk aversion, leading banks to pass on higher interest rates to borrowers. They find that this spread plays a major role in explaining interest rate changes in consumer and mortgage loans in Czechia (Gregor and Melecký, 2018). Ashraf (2021) examines the World Uncertainty Index (WUI) to determine that a one standard deviation increase in the index raised bank loan interest rates by almost 21 basis points. Uncertainty events, such as political events and turmoil influences the volatility of exchange rates of the involved countries (Krol, 2014). In the case of emerging economies that are less integrated, the economic policy of the home country alone impacts the exchange rate volatility (Krol, 2014). When lender countries experience growth, they will be more likely to engage in cross-border lending as domestic excess liquidity increases (Jeanneau and Micu, 2002). Banks and other financial institutions may be willing to expose themselves to riskier economies and engage in international lending. Jeanneau and Micu (2002) use the risk premium on BBB rated corporate bonds to be a proxy for risk aversion and note that when the premium grows, presenting decreased risk appetite, international lending decreases. BBB rated bonds represent low investment grade bonds and as such, a significant yield premium is required when investor risk appetite is low. Cerutti et al. use the Chicago Board Options Exchange's (CBOE) volatility index, the VIX, as an uncertainty measure, and note that increases in the index had significant negative effect on bank flows (Cerutti et al., 2014).

2.3.1.3 Structural and Regulatory Factors

Structural and regulatory factors are also major supply-side determinants of loan interest rates, both domestically and internationally (Müller and Uhde, 2013). As the cost of borrowing reflected through money market rates and treasury bills respond to the official policy rate set by a country's financial regulator, lenders must anticipate several factors when passing on the underlying rate to borrowers to properly account for added risk (Castro and Santos, 2010). Castro and Santos (2010) highlight these factors to be bank specific characteristics such as size, liquidity and capital ratios. Nițescu and Anghel (2023) look at the determinants of interest rates in bank lending in 20 countries and determine factors that play a role, both in the short-term and the long-term. Long-term, a bank's ratio of NPL to total loans is the largest supply-side factors in determining the loan interest rates given by banks. A rise in the NPL ratio leads to increased interest rates (Nițescu and Anghel, 2023). Short-term, however, they show that only a country's financial freedom index significantly impacts interest rates. A one point increase in the financial freedom index, resulted in a 3.8 basis point increase in the interest rate, presumably due to market dynamics not being suppressed artificially (Nițescu and Anghel, 2023). That is to say, a country with a low financial freedom index may pressure banks to artificially keep interest rates low or improperly assess the riskiness of loans.

Emter et al. (2024) note that several other factors can explain cross-border lending activity. They highlight distance, trade linkages, financial linkages, trade invoicing patterns, and offshore financial centers. Müller and Uhde (2013) look at cross-border bank claims from 13 Organisation for Economic Co-operation and Development (OECD) countries towards 51 emerging market economies. They find that in OECD countries with high banking market concentration, that is to say that a smaller number of large banks hold significant power, cross-border lending towards emerging markets is not seen as a priority as they do not face fierce domestic competition (Müller and Uhde, 2013). As those banks control most of the domestic market, they are able to enjoy high profit margins and do not face the need to look internationally for riskier lending opportunities.

The distance between lender and borrower country affects lending activity. Emter et al. (2024) note that more so for the euro than the dollar, lender countries will lend far less to borrower countries further away, possibly due to decreased informational transparency. Muller and Uhde (2013) also mention geographical distances as a major determinant of cross-border lending in their analysis of trade flows through the lens of the gravity model, which explains trade flows based on the distance between two countries and their respective economic measures. This relation is shown in the below equation, where F represents trade flow, G is a constant, M are economic measures and D is the distance between two countries:

$$F_{ij} = G\frac{M_i^{\beta_1} M_j^{\beta_2}}{D_{ij}^{\beta_3}}\eta_{ij} \tag{1}$$

Economic measures M most often represent the GDP of two countries. Muller and Uhde (2013) find that the GDP of the source country plays a positive role in the volume of claims, with a one point increase in the source country's GDP leading to a 80 basis point increase in claims (Müller and Uhde, 2013). However, they find that GDP growth in the source country leads to slightly fewer claims. Distance has a negative effect on bank claims, with a unit increase in the distance resulting in a 55 to 65 basis point reduction in the number of bank claims (Müller and Uhde, 2013).

2.3.2 Demand-Side Factors

2.3.2.1 Currency Factors

As opposed to domestic lending, cross-border lending often adds the element of currency risk, where the currencies in the lender and borrower country are different. Such currency mismatch risks are major factors that banks consider when lending cross-border (Buch and Lipponer, 2010). In Central and Eastern Europe, this effect is also largely present, with foreign banks wanting to minimize their exposure to currency risk (De Haas and Van Lelyveld, 2010). Most often, currencies are freely traded and as such, markets can reflect risks, such as the aforementioned political risk, or other macroeconomic effects, in the price of the borrower country's currency relative to another currency. These risks can be broadly categorized as interest rate differentials and exchange rate volatility, which are fundamentally related through the interest rate parity (IRP) theory.

IRP theory is a fundamental relation that connects interest rates, spot exchange rates and foreign exchange rates. Two variations of IRP theory exist with slightly different assumptions: covered interest rate parity (CIRP) and uncovered interest rate parity (UIRP). CIRP theory states that the interest rate differential between two countries should be reflected in the form of a premium or a discount between the spot exchange rate and the forward exchange rate (Nirmali and Rajapakse, 2016). UIRP, on the other hand, looks at a future expected spot exchange rate, rather than a forward exchange rate (Wu and Chen, 1998). The inability to hedge, or cover, against exchange rate risk results in the latter's name. This relation (CIRP:$\lambda = 0$, UIRP:$\lambda = 1$) can be shown numerically as follows, where $F_{t,T}$ is the forward exchange rate at time t for delivery at time T, $E_t[S_T]$ is the expected spot exchange rate at time T as of time t, S_t is the spot exchange rate at time t, and i_a and i_b are the interest rates in countries A and B respectively:

$$(1-\lambda)F_{t,T} + \lambda E_t[S_T] = S_t \cdot \left(\frac{1+i_b}{1+i_a}\right) \tag{2}$$

If the above relation holds for CIRP, there is no arbitrage opportunity between the two currencies and the cost of borrowing in a foreign currency should be equal to that of borrowing domestically (Delis et al., 2022). This can be shown mathematically through the set of equations in 3:

$$\begin{aligned}
\text{Domestic Investment:} \quad & X(1+i_a) \\
\text{Foreign Investment (with forward contract):} \quad & \frac{X}{S_t}(1+i_b)\cdot F_{t,T} \\
\text{No Arbitrage (CIRP):} \quad & X(1+i_a) = \frac{X}{S_t}(1+i_b)\cdot F_{t,T} \\
\text{Simplifying:} \quad & 1+i_a = \frac{(1+i_b)\cdot F_{t,T}}{S_t} \\
\text{Rearranging:} \quad & F_{t,T} = S_t \cdot \left(\frac{1+i_a}{1+i_b}\right)
\end{aligned} \tag{3}$$

When IRP does not hold, an investor can benefit from this by borrowing currency in a lower interest rate regime and investing in a higher interest rate regime, whilst hedging against exchange rate risk using forward contracts. Theoretically, IRP should result in a certain amount of stability in exchange rates. However, empirically, this relationship is rather weak and exchange rate volatility can occur regardless of stable interest rate differentials (Wu and Chen, 1998). These deviations can be primarily explained by balance sheet constraints of financial institutions and imbalances in the supply and demand of different currencies internationally (Du et al., 2018).

The setting of interest rates at the central bank level allows countries or economic zones to either expand or contract spending in order to deal with inflationary dynamics. When economies experience inflationary pressure, they may opt to make changes to their monetary policy by increasing interest rates, making borrowing more expensive and saving more attractive, effectively putting downward pressure on inflation. As a result, changes in interest rates directly affect the attractiveness of currencies. The difference between the interest rates of two currencies is referred to as an interest rate differential.

Following the collapse of the Bretton Woods system in 1971, which enforced currency denomination to be pegged to the US dollar for 44 countries, major countries adopted a floating exchange rate mechanism, which called for exchange rates to be determined freely by the market (Muhammed Rafi and Ramachandran, 2018). Since then, exchange rates have played a major role in both international trade volume and cross-border capital flow (Jehan and Hamid, 2017). Delis et al. (2022) break down exchange rate risk into two categories: demand-side risk and supply-side risk. The former refers to foreign entities borrowing in the lending entity's currency, transferring risk onto the borrowing entity. The latter describes a situation in which an entity lends to a foreign entity in the borrower's currency, transferring risk onto the lending entity. While various macroeconomic factors play a role in exchange rate determination, the interest rate differential between the involved currencies often are a major determinant (Muhammed Rafi and Ramachandran, 2018). Higher exchange rate volatility generally pushes risk-averse players away from foreign trade due to the unpredictable nature of profits between the agreement date of a trade and the eventual settlement (Ozturk, 2006).

In their paper on the effects of exchange rate volatility on bank lending activity through impulse response analysis, Buyun (2024) notes that an exchange rate volatility shock has a significant and negative effect on the volume of bank loans. Such a shock accounted for roughly 20% of the variance in lending volume for up to five periods following the event (Buyun, 2024). When looking at the rates that banks offer to firms, a company's foreign currency exposure results in significantly higher loan spreads (Francis and Hunter, 2012). For a standard deviation increase in positive exposure, net importers, who are exposed to foreign currencies, experience 27 basis point increases in their lending rates for developed country currencies and 39 basis point increases for emerging market currencies (Francis and Hunter, 2012). However, for firms with negative exposure to foreign currencies, lending rates only showed a 15 basis point decrease for a standard deviation decrease, highlight the asymmetric risk that banks put on exchange rate dynamics (Francis and Hunter, 2012).

Delis et al. (2022) find that when lending occurred in a currency other than that of the lender, a standard deviation increase in exchange rate volatility resulted in a 5.5 to 16.1 basis point increase in the loan spread. This spread is accentuated during periods of currency crises. During the Asian financial crisis in the late 1990s, when Asian currencies rapidly devalued, loan spreads to lenders in affected countries rose by 113 basis points (Delis et al., 2022). Contrary to this finding, Francis and Hunter (2012) found that during this period, firms with positive exposure to Asian currencies did not experience significantly higher loan spread. It should be noted that the two studies compare slightly different scenarios, where the former looks at loans to borrowers in the affected regions and the latter looks at loans to domestic borrowers with exposure to currencies from the affected regions. This discrepancy may be explained by the fact that domestic firms hedge their foreign currency exposure and thus, did not experience significantly higher risk during the currency downturn (Francis and Hunter, 2012).

Appreciation of borrower country currencies may encourage cross-border lending due to the perceived attractiveness of borrower balance sheets, resulting in greater risk-taking by lenders (Bruno and Shin, 2015). Odionye et al. (2023) also highlight that exchange rate depreciation, in combination with a substantial interest rate differential, can lead to a boost in cross-border inflows. However, significant exchange rate volatility leads to a multitude of issues for foreign lenders. In their study of foreign direct investment in Latin American and the Carribean, Dal Bianco and Loan (2017) find that exchange rate volatility reduced cross-border inflow by roughly 35% of GDP. This is in accordance with other studies on the impact of exchange rate volatility on flow into emerging markets. Exchange rate volatility in Ghana also deterred foreign direct investment into the country (Adjei-Mantey and Itoigawa, 2020). Volatility of any kind reduces the margins of financial institutions as they experience increased hedging costs. When lending money to foreign borrowers, hedging using financial contracts take place to protect lenders from currency risk. This can be accomplished using forward contracts, futures contracts, or options, and allows the lender to lock in a fixed exchange rate prior to lending to ensure protected downside. In the banking sector in Iran, a percent increase in exchange rate volatility saw a 7.7 basis point decrease a bank's return on investment (Ebrahimi and Heidari, 2017). Dal Bianco and Loan (2017) emphasize that exchange rate volatility is the main driving force attracting cross-border inflows, with interest rate differentials taking on a moderating role. In addition to the decrease in cross-border flow from exchange rate volatility, which exerts upwards pressure on interest rates, financial institutions also have to place a premium to ensure that the increased risk and hedging costs are accounted for.

2.3.2.2 Macroeconomic Factors

In their study of long-term determinants of interest rates in bank lending, Nițescu and Anghel (2023) find that the unemployment rate, the real effective exchange rate index, and inflation play a role in determining the interest rates given by banks. A rise in unemployment and inflation both led to increased interest rates, with inflation having the biggest effect (Nițescu and Anghel, 2023).

Cerutti et al. (2014), find that lagged GDP growth and inflation metrics are able to explain cross-border flows to banks and non-banks. For all periods bar 2001-2006, lagged GDP growth resulted in statistically significance increases in cross-border claims to banks and non-banks, potentially resulting in lower lending rates (Cerutti et al., 2014). Lagged inflation rates show an inverse correlation to cross-border claims to banks between 1990 and 2012, but did not produce statistically significance results for claims to non-banks (Cerutti et al., 2014).

In their study of bank lending rates in Turkiye, Yildiz (2020) finds that the M2 money supply of the country has a statistically significant inverse relation mortgage, consumer, and vehicle loan rates. The study finds no statistically significant relation to lending rates for inflation and the performance of gold in any loan category (Yıldız, 2020).

Spahija-Gjikolli et al. (2025) look at bank lending rates over several term lengths in Kosovo to determine the effects of GDP, population size and inflation rates on lending rates. They find that for long term loans (over 10 years), GDP has a statistically significant inverse relation (-0.1) to lending rates, whilst inflation has a positive relation (0.35) to lending rates (Spahija-Gjikolli et al., 2025). For loans with a term length shorter than 10 years, population size has a negative relation to interest rates (Spahija-Gjikolli et al., 2025. That is to say, bank lending rates will fall anywhere from 1.14% to 1.36% for every percent increase in population size. In their study of bank lending rates internationally, Ivakhnenkov et al. (2020) find that inflation rates are positively correlated to bank lending rates whilst GDP per capita shows an inverse relationship.

2.4 Interest Rate Determinants in P2P Lending

Interest rate determination for P2P loans can largely be broken down into two selling mechanisms: the reverse auction process and posted-price sales. The reverse auction mechanism allows potential lenders to specify their minimum desired interest rate during a specified auction period. No real consensus has been reached on whether the reverse auction process provides borrowers with lower interest rates (Dietrich and Wernli, 2016). On one hand, the reverse auction process incentivizes borrowers to reveal as much information as they can about their financial situation to appeal to lenders. On the other hand, retail lenders often lack the necessary credit risk models to properly evaluate the loans, and this may lead to instances of the winner's curse, where the final interest rate does not properly reflect the risk associated with the loan. Posted-price mechanisms, on the other hand, rely solely on the seller, or lending entity in P2P markets, to specify a loan amount and associated interest rate. While auction mechanisms have historically been dominant in electronic commerce, they have recently lost their appeal (Wei and Lin, 2013). In line with the reasoning associated with the winner's curse, Wei and Lin (2013) show that empirically, the switch from an auction mechanism to a posted-price mechanism on *Prosper.com*, a leading US-based P2P lending platform, yielded lenders with roughly 1% higher interest rates than they would have gotten using an auction. Additionally, posted-price loans had a 20% increase in funding probability using the updated mechanism (Wei and Lin, 2013). Dietrich and Wernli (2016) raise the point that posted-price mechanisms, which rely on professional lenders with data-driven models to set interest rates, may be superior to reverse auctions from a risk-return perspective. However, Wei and Lin (2013) show that this may not necessarily be the case as loans under the posted-price regime exhibit roughly a 2% increase in default rates and argue that the increased interest rate may not necessarily result in excess returns.

Under a posted-price regime, the P2P platform or loan originators assess the relevant risks using sophisticated credit risk models. In such a scenario, the platform acts very similarly to large financial institutions such as banks that lend internationally. A parallel can be drawn between P2P platforms in this case and these lenders discussed in the previous section. Much like for banks, P2P platforms and loan originators will take currency risk into account in their risk models, making exchange rate volatility a key factor they must consider for cross-border P2P loans. When looking at Figure 2, showing the flow of funds on loans posted on Mintos, it can be seen that lending companies pass on interest rate r_2 to lenders while receiving interest rate r_1 from borrowers. Interest rate r_1 will accrue in the borrower's local currency, whereas interest rate r_2 is paid back to lenders in Euro. In order to protect lenders from exposure to a foreign currency, as well as ensuring that they are able to turn a profit, lending companies have to select r_1 and r_2 carefully. This additional risk will be passed on to lenders through the form of a higher interest rate of P2P loans.

$H_{1,1}$: Exchange rate volatility between the borrower country currency and the lender currency will result in higher P2P loan interest rates

Much like in the previous section discussing interest rate determinants in traditional lending, this section will be divided into supply-side determinants and demand-side determinants of P2P loan interest rates.

2.4.1 Supply-Side Factors

Much like for international lending, cost of capital plays a role in determining the interest rates of P2P loans. Dietrich and Wernli (2016) look at the risk free rate (3 year Swiss Government Bond yield) and the 3 month stock market index performance (Swiss Market Index) to assess the willingness of lenders to fund loans. Liu et al. (2021), who focus on the United States, use a very similar composition of factors by looking at the federal funds rate, the S&P500 return rate, and the performance of a fintech index. Both studies observe similar effects on the interest rate of P2P loans by these factors. Dietrich and Wernli (2016) show that a standard deviation increase (0.54) in the 3 year Swiss Government Bond yield results in a 127 basis point increase in interest rates but a standard deviation increase (5.85) in the Swiss Market Index results in a 28 basis point decrease in the associated interest rate (Dietrich and Wernli, 2016). Liu et al. (2021) find that a standard deviation increase (0.78) in the federal funds rate resulted in a 39 basis point increase in the interest rate. Additionally, they found that a standard deviation increase (5.67) in the S&P500 return rate results in a 39 basis point increase in interest rate, whereas a standard deviation increase (6.19) in the fintech index resulted in a 6 basis point decrease in the interest rate (Liu et al., 2021). An increase in the fintech index may signal increased confidence in such technologies by lenders, leading to a lower risk perception and thus, lower interest rates.

2.4.2 Demand-Side Factors

2.4.2.1 Loan Characteristics

Loan specific factors, such as the duration of the loan, the amount requested, and the number of loans available for funding, positively correlate to the interest rate associated with the loan (Dietrich and Wernli, 2016). Dietrich and Wernli (2016) show that a standard deviation increase in the loan amount (11,995) and the loan duration (7.56), resulted in an interest rate increase of 42 basis points and 31 basis points, respectively. On the other hand, Ahmed (2024) and Hietala (2016) find that the duration or term of the loan is inversely correlated to the interest rate of the loan in their research of Dutch and Finnish P2P lending platforms, respectively. Hietala (2016) argues that the interest rates associated to longer term loans do not include a risk premium to address the higher probability of default associated with a longer repayment horizon. Ahmed (2024) and Hietala (2016) also find that the loan amount has either no effect or statistically insignificant effects on the interest rate of the loan. However, most research shows the opposite result of loan duration and loan amount resulting in higher interest rates. Darmon et al. (2018) show that a standard deviation increase (12.74) in the duration of a loan results in a 246 basis point increase in the resulting interest rate. Similarly, a standard deviation increase (56.91) in the loan amount results in an 86 basis point increase in the interest rate (Darmon et al., 2018). Additionally, when considering a traditional yield curve, the time to maturity of an instrument should be positively correlated to its yield.

Ofir and Tzang (2021) find that loans with reduced secondary market appeal demand a higher interest rate to accommodate the risk associated with this lack of liquidity. The purpose of the loan also highly affects the interest rates that borrowers pay. Liu et al. (2021) find that relative to those wanting to repay their credit card debt, those demanding loans for debt consolidation or other reasons, paid higher interest rates. Ofir and Tzang (2021) find that business loans for the services, manufacturing, commerce, real estate, and hospitality industries had lowered interest rates. On the other hand, a business loan where the industry is categorized as "other", had increased interest rates, possibly due to the elevated risk in non-traditional industries (Ofir and Tzang, 2021).

2.4.2.2 Borrower Characteristics

Kumar's (2007) study of the aforementioned platform *Prosper.com* highlights several variables that explain the interest rate of P2P loans. Loan amounts, the borrower's debt-to-income ratio, and whether or not the borrower is part of a group on the platform, all positively correlate to the associated interest rate. On the other hand, the borrower's credit score, homeownership status, or endorsement from a trusted member on the platform, all lead to lowered interest rates (Kumar, 2007). The homeownership status and debt-to-income ratio of borrowers is repeatedly mentioned in literature as playing a role in determining the interest rates of P2P loans. Dietrich and Wernli (2016) place these factors under borrower specific factors, alongside characteristics such as the borrower's nationality, gender, marital status, and parental status. They find that homeownership results in a 73 basis point decrease in interest rate and a 10% increase in a borrower's debt-to-income ratio results in a 31 basis point increase in interest rate (Dietrich and Wernli, 2016). While the debt-to-income ratio of a borrower results in a risk premium on the loan, Kumar finds that this increase in premium is not necessarily appropriate as it does not result in a higher probability of default (Kumar, 2007). Weiss et al. (2010) and Liu et al. (2021) both determine that an elevated debt-to-income ratio is indeed a factor that plays a role in heightened interest rates. Liu et al. additionally investigate different statuses of homeownership by differentiating renters, homeowners, and home mortgage holders (Liu et al., 2021). They find that, relative to full ownership of a house, those with a mortgage on their property benefit from lower interest rates and renters experience higher interest rates. The lower perceived risk associated with mortgage holders may be due to the fact that they have active collateral (Liu et al., 2021). Weiss et al. (2010) find that retired borrowers experience higher interest rates on P2P platforms. This can be explained by the fact that they do not have consistent income, making them riskier than employed borrowers.

On platforms with posted-price regimes or in countries with more developed credit scoring systems, such as the United States, credit or risk scores play a large part in determining the interest rates of P2P loans. While Ahmed (2024) finds credit scores to be statistically insignificant, most literature agrees that a higher credit score results in lower interest rates for borrowers. In their analysis of business P2P loans, Hietala (2016) finds that a standard deviation increase (1.23) in a borrower's credit score results in a 60 basis point reduction in the associated interest rate. Darmon et al. (2018) show that a standard deviation increase (0.48) in the platform risk score results in a 22 basis point decrease in the loan interest rate. Weiss et al. (2010) show directionally similar results, with a standard deviation increase (1.96) in the borrower's credit score resulting in a 860 basis point decrease in the final interest rate of the loan. As credit scores are associated with default probability, the decreased in risk premium is appropriate and expected (Kumar, 2007). However, it is important to note that literature and P2P platforms use a variety of credit scoring method and as such, resulting interest rate decreases may not map exactly. Whilst this is the case, literature shows that the resulting interest rate decrease is directionally similar.

$H_{1,2}$**: A lower borrower entity risk score will result in higher P2P loan interest rates**

2.4.2.3 Macroeconomic Factors

Literature on the effects of macroeconomic factors on P2P interest rates is very scarce. However, much like in traditional lending, macroeconomic factors play a considerable role in determining the interest rates of P2P loans. Dietrich and Wernli (2016) find that a standard deviation increase (0.35) in unemployment results in a 152 basis point increase in interest rates. Similarly, Liu et al. (2021) find that a standard deviation increase (0.69) in unemployment results in a 17 basis point increase in interest rates. In their 2017 paper, Foo et al. (2017) look at macroeconomic determinants of P2P loan credit spreads by grade type. They define the credit spread to be the difference between the loan interest rate and the risk free rate of the same maturity. They note that for higher grade loans (A and B), the unemployment rate has a statistically significant and negative relation to the credit spread (Foo et al., 2017). Although they also examine the effects of inflation and GDP on loan credit spreads, they are unable to find statistically or economically significant results for these macroeconomic factors (Foo et al., 2017). However, as the dynamics of P2P lending and traditional lending have converged (posted-price mechanisms employ similar interest rate models to banks), it can be inferred that the effects of macroeconomic factors on traditional lending rates should hold for P2P loans as well.

3 Methodology

3.1 Sample and Data

Mintos is the largest Euro denominated P2P lending platform with a market share of around 55% (P2P Invest ApS, 2024). The platform has facilitated over 11 billion EUR in varying loan types, ranging from agricultural loans to car loans with an average interest rate of 11.65% as of May 2025 (AS Mintos Marketplace, 2025). Mintos provides historical data of 1.8 million loans. These loans span from October 23rd, 2014 to December 31st, 2024. The total number of loans per year and the yearly growth rate is shown in Table 2.

YEAR	COUNT	GROWTH RATE
2019	1,438	772%
2020	3,149	119%
2021	10,303	227%
2022	66,200	543%
2023	241,633	265%
2024	1,486,263	515%
Total	1,808,986	-

Table 2: Loan count by year on Mintos

To isolate relevant variables, the data is cleaned to only contain the following variables: issuance date, borrower country, Mintos risk score, loan type, loan interest rate, loan term, initial loan amount, and issuance currency. Missing data, as well as incorrect data, such as non-numeric numeric inputs, are removed, leaving data for just over 1.3 million loans. As this research uses loan data from Mintos in conjunction with macroeconomic data, the loans in the sample have to meet several requirements. Namely, the recipient countries must have a non-pegged and free-floating currency, and must have a domestic stock market index. In addition to this, there must be at least 12 loans per unique recipient country in a single year to ensure that a large enough sample size is available over the studied period. Table 3 shows the distributions of loans per year by country. To ensure that enough loans are studied per year, the three year period between 2022 and 2024 was chosen as the study period.

Country	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**Total**
Colombia	0	0	0	30	360	39,610	40,000
Kazakhstan	4	76	1,687	14,453	36,453	412,107	464,780
Kenya	355	436	1,110	3,820	6,600	6,274	18,595
Mexico	22	236	1,082	8,401	16,795	26,385	52,921
Poland	0	0	0	5,777	17,401	10,402	33,580
Romania	208	387	1,172	4,217	13,740	18,613	38,337
Uganda	0	0	2	227	314	8,739	9,282
United Kingdom	0	0	1	82	915	76,262	77,260
Total	-	-	-	-	-	-	734,755

Table 3: Loan Frequency by Country and Year

Upon filtering for these requirements, just over 700 thousand loans from eight different countries remained. In addition to this, there must be at least 12 loans per unique recipient country in a single year to ensure that a large enough sample size is available over the studied period. Upon filtering for these requirements, just over 700 thousand loans from eight different countries remained that met the needs of the study. The countries chosen to be studied, as well as their currency, stock market index, and the frequency of loans per year is shown in Table 4.

COUNTRY	**CURRENCY**	**STOCK INDEX**	**2022**	**2023**	**2024**	**TOTAL**	**SHARE (%)**
Colombia	COP	COLCAP	30	360	39,610	40,000	5.50
Kazakhstan	KZT	KASE	14,453	36,453	412,087	462,993	63.61
Kenya	KES	NASI	3,820	6,600	6,274	16,694	2.29
Mexico	MXN	MXX	8,401	16,795	26,315	51,511	7.08
Poland	PLN	WIG20	5,777	17,401	10,372	33,550	4.61
Romania	RON	BETI	4,217	13,740	18,613	36,570	5.02
Uganda	UGX	ALSIUG	227	314	8,739	9,280	1.28
United Kingdom	GBP	FTSE	82	915	76,217	77,214	10.61
TOTAL	-	-	37,007	92,578	598,227	727,812	-

Table 4: Currency, Stock Market Index, and Loan Frequency by Country and Year

3.2 Model Specification

The hypotheses generated in the literature review section are re-introduced here. The following hypotheses will be tested in this research:

$H_{0,1}$**: Exchange rate volatility between the borrower country currency and the lender currency has no effect or will result in lower P2P loan interest rates** ($\beta_1 \leq 0$)
$H_{1,1}$**: Exchange rate volatility between the borrower country currency and the lender currency will result in higher P2P loan interest rates** ($\beta_1 > 0$)

$H_{0,2}$**: A lower borrower entity risk score has no effect or will result in lower P2P loan interest rates** ($\beta_2 \geq 0$)
$H_{1,2}$**: A lower borrower entity risk score will result in higher P2P loan interest rates** ($\beta_2 < 0$)

A one-tailed t-test with a significance level of $\alpha = 0.05$ will be used to test the directional hypotheses. The null hypotheses will be rejected in favor of the alternative hypotheses if the p-value corresponding to each coefficient is less than 0.05 and the sign of the coefficient matches the direction specified in each alternative hypothesis. Goodness of fit will be investigated using the adjusted R^2 values, as well as assessing the residuals and performing robustness checks on the model.

The equation used in this paper builds on the model used by Dietrich and Wernli (4), which looks at loan-specific, borrower-specific, and macroeconomic factors and their impacts on the interest rates of domestic P2P loans by incorporating international dynamics (2016).

$$Rate_{i,t} = \alpha + \beta \times Loan_i + \gamma \times Borrower_i + \delta \times Macro_t + \epsilon_{i,t} \tag{4}$$

A regression equation (5) can be derived from the variables mentioned in Table 5. The focus of the research is on the impacts of loan originator creditworthiness, or risk score, and currency risk on the interest rate of a cross-border P2P loan. In order to control for loan specific factors, as well as other macroeconomic and risk factors, control variables are carefully chosen based on literature.

$$\begin{aligned} INTR_{i,c,o,t} = \beta_0 + \beta_1 FXV_{c,t-2} + \beta_2 RISK_{o,t} + \gamma(&TERM_{\ln,i}, AMNT_{\ln,i}, D_{i,CAR}, \\ &D_{i,BUSI}, D_{i,SHORT}, DIST_c, VIX_{t-4}, INFL_{c,t-2}, UNEMP_{c,t}, \\ &GDP_{c,t-4}, STOCK_{c,t-4}, STX50_{t-4}, ECBR_{t-2}) + \epsilon_{i,c,o,t} \end{aligned} \tag{5}$$

Where each symbol denotes: i = individual loan level characteristics; c = country level characteristics; o = loan originator characteristics; t = time; $t-2$ = variable lagged by 2 quarters; $t-4$ = variable lagged by 4 quarters; β_0 = intercept of the regression model; β_{1-4} = regression coefficients for the independent variables; γ = control variables; and ϵ = the error term. All of the variable abbreviations are denoted in Table 5.

Natural logarithmic values of loan term ($TERM_i$) and loan amounts ($AMNT_i$) will be taken to deal with extremely right-skewed distributions. Taking logarithmic values for these explanatory variables allows for compression of long tail values and improved interpretation.

3.2.1 Model Specification Tests

Heteroskedasticity Test

Heteroskedasticity occurs when the error terms of the regression model do not exhibit constant variance, resulting in biased estimation of the standard errors. This results in biased test statistics and confidence intervals, hindering interpretation of the model. White's test for homoskedasticity was carried out to examine the variance of the residuals. White's test was preferred over the Breusch-Pagan test due to the large sample size and the potential non-linearity of residuals. The null hypothesis of White's test indicates that the variance of residuals is constant (homoskedasticity) and the alternate hypothesis indicates the presence of non-constant residual variance (heteroskedasticity). The test indicated strong evidence against the null hypothesis and as such, heteroskedasticity is present in the data. Robust standard errors were used in the regression to combat this and yield interpretable standard errors.

Normality Test

Normality of residuals can be tested both numerically and visually. A Jarque-Bera test is carried out to test residual normality numerically. The null hypothesis of the Jarque-Bera test indicates normal distribution of the residuals, with skewness equal to zero and kurtosis equal to three. The alternative hypothesis indicates non-normal residuals. The test indicates a very strong rejection of the null hypothesis, indicating non-normality. However, as the sample contains 727,812 observations, the test may be too sensitive and indicate that even small deviations from normality as problematic. In addition to the Jarque-Bera test, a QQ plot was generated to visually assess normality (Figure 4).

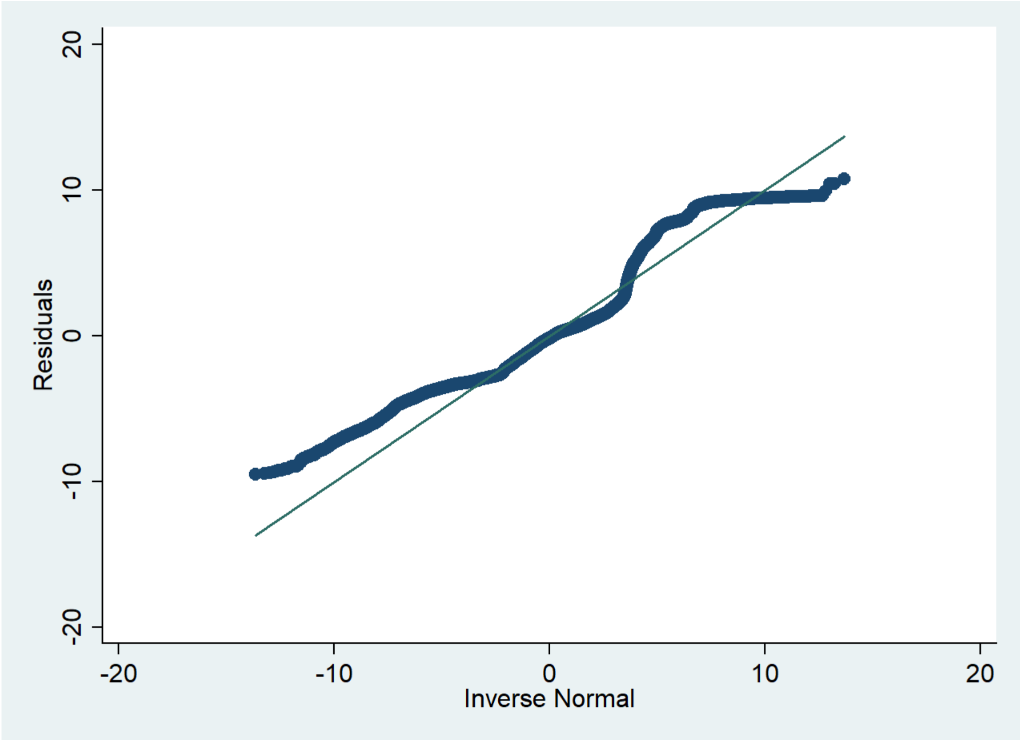


Figure 4: QQ Plot of Residuals

The QQ plot shows deviations in the tails of the distribution, indicating skewness and kurtosis problems. To deal with non-normality, significance of coefficients will be assessed using z-values, which use the normal distribution in combination with t-values to assess significance. In addition to this, a median regression will be carried out as a robustness check to assess the effects of the tail deviations.

Multicollinearity Test

Multicollinearity refers to the ability of a variable to predict another variable in the model accurately. When multicollinearity is present, regression coefficients exhibit instability and fluctuate rapidly in response to small data changes. The variance inflation factor (VIF) is used to measure the degree of multicollinearity presence between variables in a model. Although no clear thresholds exist for how high of a VIF value is considered problematic, values above 10 tend to be considered as too high. All variables in the regression have VIF values below 5 with the mean VIF value of the variables sitting at 2.34. From this, it is concluded that multicollinearity is not present in the regression variables to a problematic degree.

3.3 Variable Measurement

3.3.1 Dependent Variable

This paper will look at the impacts of several factors on the interest rates of P2P loans on Mintos. As Mintos uses a posted-price system, rather than a reverse auction mechanism, the interest rates are set by the platform based on their risk models. In addition to this, interest rates on Mintos are fixed, as opposed to variable, and do not change for the duration of the loan. Platform fees will not be considered when looking at returns.

P2P loan interest rates are of significant importance as they serve as an easy risk gauge for investors who are looking to allocate their funds in Mintos' loan offerings. He et al. (2021) note that investors are able to distinguish between good and bad projects based on their interest rates and avoid overly elevated interest rates. They also note that interest rate levels on P2P platforms fall as they become larger, presumably due to increased measures against overly risky loans (He et al., 2021). As interest rates serve to inform investors on the riskiness of P2P loans, it is paramount that they price in all possible risks associated with the loan.

3.3.2 Independent Variables

From the literature review looking at determinants of interest rates in P2P and traditional bank lending, several variables can be isolated for analysis. Factors that influence cross-border lending flows and claims are also assumed to impact resulting interest rates due to supply and demand dynamics, as shown in Figure 3.

The variables that impact the interest rate of a cross-border P2P loan are shown in Table 5. These factors are split into four categories: loan factors, borrower factors, currency factors, and macroeconomic factors. Since borrower factors other than the loan originator risk score are not known on Mintos, this is the sole variable in this category. The sole variable under the currency risk category is the exchange rate volatility of the currency pair between the borrower country currency and the Euro.

In order to analyze the effects of currency risk and the creditworthiness of loan originators, the independent variables are chosen to be the risk score of the loan originators and the exchange rate volatility.

The current and historical risk scores are provided by Mintos along with the corresponding loan information. Currency volatility will be measured using historical volatility with data sourced from various financial terminals. These are yet to be determined and will differ based on the currency of choice.

Historical risk scores are provided by Mintos alongside other loan specific information such as the interest rate, term, amount, and purpose of the loan. Macroeconomic and currency factor variables are sourced from LSEG Workspace and central bank databases. As shown in Table 5, several variables are transformed in order to facilitate analysis. Natural logarithms of loan terms (TERM) and amounts (AMNT) are taken to deal with skewness. Exchange rate volatility (FXV) is taken to be the 30 day rolling average of the standard deviation of daily logarithmic returns. The borrower country stock index performance (STOCK) and source country stock index performance (STX50) are taken to be the logarithmic value of their daily returns.

Table 5: Factors Influencing Interest Rates on Cross-Border P2P Loans.

VARIABLE	ABB.	DESCRIPTION	MEASURE	SOURCE	EXP. EFFECT
DEPENDENT VARIABLE					
Interest Rate	INTR	Annual Euro interest rate received by the lender	%	MINTOS	
INDEPENDENT VARIABLES					
Borrower Factors					
Mintos Risk Score	RISK	Mintos risk score assigned to different loan originators where 1 represents the most risk and 10 represents the least risk	1-10	MINTOS	–
Currency Factors					
Exchange Rate Volatility	FXV	30 day rolling exchange rate volatility against EUR at time of loan origination	$STD\left(ln\left(S_t^{X/EUR}\middle/S_{t-1}^{X/EUR}\right)\right)$	LSEG	+
CONTROL VARIABLES					
Loan Factors					
Loan Term	TERM	Loan duration in months	$ln(MONTHS)$	MINTOS	+
Loan Amount	AMNT	Loan amount in Euros	$ln(EUR)$	MINTOS	+
Loan Purpose	CAR/BUSI/ SHORT	Dummy variable for different loan purposes: car loans, short-term loans, business loans (personal loans are dropped as they are the most common)		MINTOS	mixed
Macroeconomic Factors					
Unemployment Rate	UNEMP	Quarterly unemployment rate of recipient country at time of loan origination	%	LSEG	+
Inflation Rate	INFL	MoM inflation rate of recipient country at time of loan origination	$(\Delta CPI_t^M / CPI_{t-1}^M) \times 100$	LSEG	+
GDP Growth Rate	GDP	QoQ GDP growth of recipient country at time of loan origination	$\left(\Delta GDP_t^Q \middle/ GDP_{t-1}^Q\right) \times 100$	LSEG	–
Borrower Country Stock Index Performance	STOCK	30 day rolling stock index performance of recipient country at time of loan origination	$ln\left(P_t^{EUR_t}\middle/P_{t-1}^{EUR_{t-1}}\right)$	LSEG	–
Lender Country Stock Index Performance	STX50	30 day rolling stock index performance of lender country at time of loan origination	$ln\left(P_t/P_{t-1}\right)$	LSEG	+
ECB Policy Rate	ECBR	Annual ECB policy rate (source country r_f) at time of loan origination	%	ECB	+
Distance	DIST	Geographical distance between source and recipient countries	KM	GOOGLE MAPS	+
VIX	VIX	7 day rolling CBOE volatility index at time of loan origination		LSEG	+

3.3.2.1 Lagged Effects of Macroeconomic Indicators

Macroeconomic indicators often have a leading or lag effect on other aspects of the economy. The timescale of these effects are a subject of debate but several studies attempt to quantify these lags. In their paper on macroeconomic determinants of bad loans in Italian banks, Bofondi and Ropele (2011) argue that most indicators should be lagged between two to four quarters, except unemployment, which already acts as a lagging indicator. They argue that the GDP lags bad loan presence by four quarters, the risk free rate lags by three quarters, stock performance lags by three quarters, and inflation lags by two quarters (Bofondi and Ropele, 2011). Another paper on the effects of macroeconomic indicators on NPLs states that four quarters is the most explanatory lag (Szarowska, 2018). This study looks at unemployment, GDP, inflation, nominal exchange rates, lending rates, and government debt to explain the lagged emergence of NPLs (Szarowska, 2018). In their paper on macroeconomic determinants of loan defaults in the US P2P market, Nigmonov et al. (2022) determine two quarters to be the optimal lag to explain loan defaults.

Although the above papers explain loan defaults and NPL/bad loans, rather than lending rates, they will be used as a proxy for macroeconomic lag factors for the sake of simplicity. Exchange rate volatility (FXV) and the VIX are not lagged as they are forward looking indicators that reflect immediate changes in perceived risks. These should inform interest rate decisions in real time, rather than with a delay. Looking at all three studies, the following lag factors will be implemented to account for slow transmission of monetary policy and macroeconomic indicators:

MACROECONOMIC FACTOR	LAG FACTOR (QUARTERS)
UNEMP	0
INFL	2
GDP	4
STOCK	4
STX50	4
ECBR	2
FXV	0
DIST	N/A
VIX	0

Table 6: Macroeconomic Lag Factors

3.3.3 Control Variables

To isolate the effects of variables, the analysis will control for variables related to loan factors, such as the loan duration and the loan amount, as well as non-currency macroeconomic effects. When examining macroeconomic predictors, the potential for endogeneity issues is very high due to the presence of highly correlated predictors. A comprehensive inclusion of variables is ensured to prevent any predictors from being omitted.

The analysis will also control for geographic distances between source and recipient countries. As information on the whereabouts of Mintos users is not available and complex to process, Germany was chosen as the center point from which geographical distances will be taken. Germany was chosen for its economic importance within Europe and its relatively central location in Western Europe. Table 7 shows the distances of the recipient countries covered in the analysis from the chosen central point of Germany.

COUNTRY	DISTANCE (KM)
Colombia	9,248
Poland	609
Romania	1,216
United Kingdom	1,036
Kenya	6,235
Kazakhstan	3,997
Mexico	9,465
Uganda	5,888

Table 7: Geographic Distances in Kilometers from Germany to Recipient Countries

4 Results

4.1 Descriptive Statistics

Table 8 provides the descriptive statistics of loan characteristics such as the interest rate, term length, and loan amount, as well as the Mintos risk score. Interest rates on Mintos range from 6.00% to 23.90% with an average rate of 13.44%. Mintos risk scores, which range from 1 to 10 (with 10 being the highest rating), are between 5.50 to 8.90 in the sample. A higher Mintos risk score indicates a loan with less risky loan originator characteristics. Most loan originators have a risk score around the 6.00 mark. The term length ($TERM_{ln}$) and loan amounts ($AMNT_{ln}$) are both logarithmic measures. The descriptive statistics for the raw values of these variables (TERM; AMNT) are given below their corresponding logarithmic measures. Most loans have a term length of 1 month and a mean length of 17.41 months. The term length ranges from 1 month to 120 months, with a standard deviation of 25.58 months. Logarithmically, this corresponds to a term length range of 0,00 to 4.79, with a median term of 0.00 and a mean term of 1,50. Loan amounts range from 22.59 EUR to 156,550 EUR, with a median amount of 378 EUR and a mean amount of 700 EUR. Logarithmically, this corresponds to loan amounts between 3.12 EUR and 11.96 EUR, with a median amount of 5.93 EUR and a mean amount of 5.87 EUR.

VARIABLE	OBS	MEAN	MEDIAN	MIN	MAX	STD DEV
INTR	727,812	13.44	13.50	6.00	23.90	3.52
RISK	727,812	6.34	6.10	5.50	8.90	0.63
$TERM_{ln}$	727,812	1.50	0.00	0.00	4.79	1.72
TERM	727,812	17.41	1.00	1.00	120.00	25.58
$AMNT_{ln}$	727,812	5.87	5.93	3.12	11.96	1.11
AMNT	727,812	699.30	377.90	22.59	156,549.60	1,629.24

Table 8: Loan Descriptive Statistics

A QQ plot can be created for the dependent variable (INTR) to assess its normality. The plot shows deviations from a normal distribution at the tail ends of the distribution. As mentioned previously, robust standard errors, as well as z-values, will be used to combat issues around non-normality and heteroskedasticity.

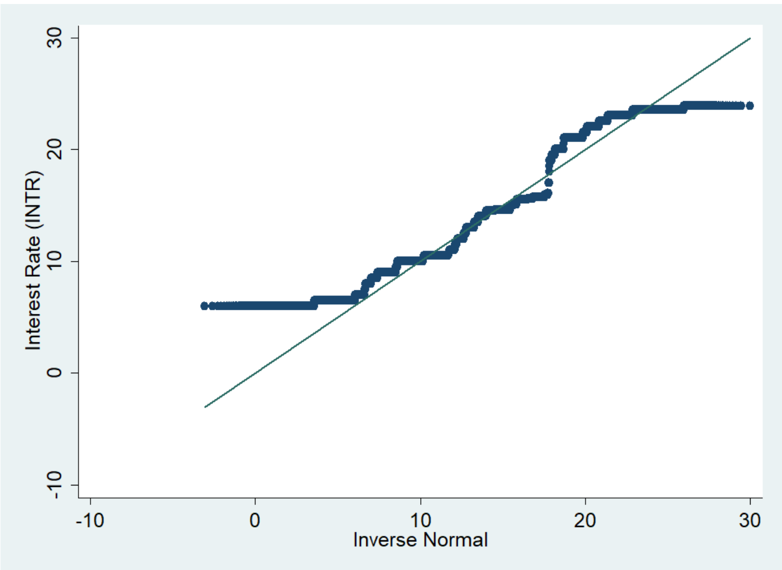


Figure 5: QQ plot of dependent variable

Table 9 shows the distribution of loans by purpose, as well as the mean interest rate associated with the loan type. Business loans have the lowest interest rates and short-term loans have the highest interest rates on average. Personal loans are dropped from the regression as they represent the largest share of the loan types.

LOAN PURPOSE	COUNT	SHARE (%)	MEAN INTEREST RATE
Business Loan	1,703	0.23	10.0%
Car Loan	20,818	2.86	12.3%
Personal Loan	353,975	48.64	13.1%
Short-Term Loan	351,316	48.27	13.9%
Total	727,812	-	-

Table 9: Loan count by type and corresponding interest rates

Table 10 provides the descriptive statistics of macroeconomic factors used in the research by country. The average daily exchange rate volatility against the Euro ranges anywhere from 0.12 to 0.84, with the Colombian peso being the most volatile.

Monthly inflation rates (INFL) range from -0.65% to 3.65%. The studied period was characterized by high inflation readings around the globe due to elevated spending during the COVID-19 pandemic and geopolitical tensions. Most countries saw inflation peak during late-2022 to early-2023, followed by a relatively sharp decline. It is possible that the inflation data contains outliers that may bias the model.

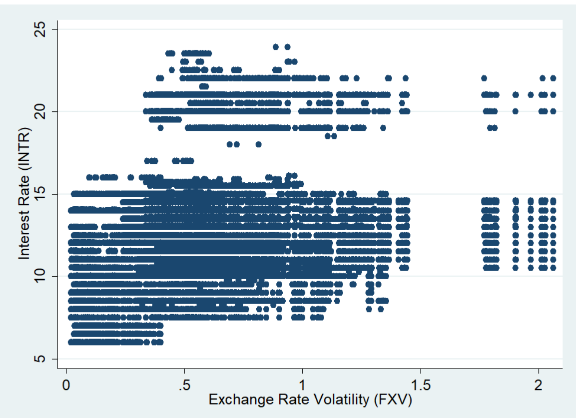
Unemployment rates (UNEMP) range from 2.47% to 12.60%. This reflects the wide range of development within borrower countries on Mintos. Colombia and Uganda have the highest average unemployment rates at 10.51% and 10.57%, respectively. These figures are far larger that the average unemployment rate figures seen in the remaining countries, which range from approximately 3% to 5%, in line with most target rates of around 4%.

GDP growth rates (GDP) range from -3.22% to 13.00%, showing both slowing growth and extreme expansion of the economies of the research countries. All but one country had a period of economic slowdown during the studied period.

Country specific daily stock index performance ranges from -1.68% to 1.23%. As is normally the case for financial return data, their means are centered about zero. The European stock index, STOXX50 (STX50), has daily returns ranging from -0.72% to 0.69%. Interestingly, the index has relatively high volatility when compared to some of the emerging market countries in the study.

In general, a VIX value of under 20 reflects stability in the US market and thus a relatively increased risk appetite. During the studied period of 2022 to 2024, the VIX ranged from 12.30 to 34.15, showing both periods of stability and instability. However, on average, VIX reflected relative stability with a mean value of 20.98. In mid-2024, the VIX experienced its largest ever one day spike due to dynamics in the S&P500 options market, potentially resulting in outliers in the data. During the year, the VIX experienced heightened levels due to both recessionary fears in the US and increased geopolitical tensions. 2023 was generally characterized by relative stability in the markets, which could balance the averages.

Finally, ECB policy rate, which is used as a proxy for the risk free rate in the source region, ranges from -0.50% to 4.00%. The period of study saw the ECB hike rates in order to combat latent inflation following the global pandemic and geopolitical turmoil. The standard deviation of 1.94% shows the rapid rate hiking cycle undertaken by the ECB in order to manage rising inflation during the period.



(a) FX Rate Volatility against Loan Rate Percent

(b) Mintos Risk Score against Loan Rate Percent

Figure 6: Scatter plot of independent variables against dependent variable

Scatter plots are created to visualize the relation between the independent variables (FXV and RISK) and the dependent variable (INTR). Although there is a linear trend of sorts, both plots show a lot of deviations from possible linearity. This may be due to the discrete properties of the interest rate (INTR) and the Mintos risk score (RISK), which is evident in the plots. While the plots suggest weak relations between the dependent and independent variables, further analysis using a linear regression is carried out to assess the effects of the independent variables on the dependent variable.

Table 10: Descriptive Statistics of Macroeconomic Factors by Country

VARIABLES	OBS	MEAN	MEDIAN	MIN	MAX	STD DEV
COLOMBIA						
FXV	40,000	0.64	0.63	0.35	1.13	0.15
$INFL_{t-2}$	40,000	0.59	0.50	0.25	1.78	0.27
UNEMP	40,000	10.34	10.28	9.40	11.38	0.42
GDP_{t-4}	40,000	-0.31	-0.40	-0.85	2.38	0.46
$STOCK_{t-4}$	40,000	-0.15	-0.24	-1.07	0.85	0.36
KAZAKHSTAN						
FXV	462,993	0.58	0.55	0.34	2.06	0.19
$INFL_{t-2}$	462,993	0.81	0.80	0.40	3.65	0.42
UNEMP	462,993	4.65	4.64	4.55	4.91	0.07
GDP_{t-4}	462,993	4.87	4.96	-2.09	5.39	0.63
$STOCK_{t-4}$	462,993	0.10	0.11	-1.65	1.18	0.24
KENYA						
FXV	16,694	0.55	0.52	0.28	1.08	0.16
$INFL_{t-2}$	16,694	0.56	0.50	-0.19	1.69	0.37
UNEMP	16,694	5.52	5.59	4.65	6.00	0.37
GDP_{t-4}	16,694	1.43	1.30	-0.69	3.80	0.84
$STOCK_{t-4}$	16,694	-0.17	-0.15	-1.25	0.94	0.36
MEXICO						
FXV	51,511	0.68	0.63	0.31	1.35	0.23
$INFL_{t-2}$	51,511	0.43	0.44	-0.22	1.14	0.29
UNEMP	51,511	2.83	2.79	2.47	3.80	0.22
GDP_{t-4}	51,511	0.68	0.67	-1.00	1.62	0.50
$STOCK_{t-4}$	51,511	0.02	0.01	-0.71	0.69	0.23
POLAND						
FXV	33,550	0.38	0.36	0.21	1.14	0.13
$INFL_{t-2}$	33,550	0.64	0.58	-0.13	1.42	0.43
UNEMP	33,550	2.87	2.90	2.70	3.00	0.11
GDP_{t-4}	33,550	0.57	0.17	-1.60	3.39	1.39
$STOCK_{t-4}$	33,550	0.04	0.01	-0.99	1.09	0.38
ROMANIA						
FXV	36,570	0.10	0.08	0.02	0.40	0.07
$INFL_{t-2}$	36,570	0.68	0.74	-0.11	1.41	0.37
UNEMP	36,570	3.02	3.00	2.80	3.30	0.15
GDP_{t-4}	36,570	0.73	0.70	-0.31	2.80	0.70
$STOCK_{t-4}$	36,570	0.04	0.05	-0.98	0.69	0.25
UGANDA						
FXV	9,280	0.44	0.45	0.31	0.86	0.08
$INFL_{t-2}$	9,280	0.34	0.23	-0.10	1.21	0.27
UNEMP	9,280	11.77	11.91	9.41	12.60	0.74
GDP_{t-4}	9,280	5.81	5.80	1.58	13.00	0.46
$STOCK_{t-4}$	9,280	-0.14	-0.13	-1.45	0.49	0.17
UNITED KINGDOM						
FXV	77,214	0.24	0.21	0.14	0.74	0.07
$INFL_{t-2}$	77,214	0.19	0.31	-0.40	1.64	0.33
UNEMP	77,214	4.29	4.30	3.60	4.40	0.12
GDP_{t-4}	77,214	-0.06	0.00	-0.37	7.30	0.17
$STOCK_{t-4}$	77,214	-0.03	-0.02	-0.57	0.49	0.17
GENERAL METRICS						
VIX	727,812	20.98	20.26	12.30	34.15	5.02
$STX50_{t-4}$	727,812	0.04	0.04	-0.72	0.69	0.23
$ECBR_{t-2}$	727,812	1.58	1.50	-0.50	4.00	1.94

4.2 Correlation Matrix

Table 11 provides the Pearson correlation coefficients for the variables in this study. Several papers identify the 0.80 - 0.90 mark as cutoffs, above which multicollinearity becomes a serious problem (Shrestha, 2020; Senaviratna and Cooray, 2019). Coefficients above this cutoff prove severe multicollinearity, at which point regression coefficient estimates lose their stability and reliability. In general, the Pearson correlation coefficients of the studied variables are far below this threshold. The variable pair with the highest correlation coefficient is the dummy variable indicating a short-term loan (SHORT) and the loan term length ($TERM_{ln}$)(-0.83***). Although a high correlation, the nature of the dummy variable makes this correlation evident as short-term loans are explicitly characterized by loan term length. Other pairs with relatively high correlations are $TERM_{ln}$ and $AMNT_{ln}$ (0.68***) and SHORT and $AMNT_{ln}$ (-0.64***). Again, the relation between the variables $TERM_{ln}$ and SHORT with $AMNT_{ln}$ seems intuitive as shorter-term loans, which are used for immediate purposes such as managing inventory, tend to be of lower amounts. The VIF test carried out in Section 3.2.1, shows that although these variables have relatively high correlation coefficients, they are not problematic to the overall study as they do not exhibit severe multicollinearity. All VIF values are under the commonly used thresholds of 5 to 10. The mean VIF value for all of the variables is 2.34, indicating that not significant issues of multicollinearity should be accounted for during the regression.

The Mintos risk score (RISK) is significant and negatively correlated (-0.41***) to the overall loan interest rate (INTR). This is expected as these factors should be inversely correlated. As a loan originator's risk score increases (a higher risk score is associated with a less risky loan originator), the resulting interest rate should be lower to account for the lower risk associated with the ultimate borrower and the financial health of the loan originator. Exchange rate volatility (FXV) is significant and positively correlated (0.37***) to the overall loan interest rate (INTR). This correlation is expected as heightened exchange rate volatility between the borrower and lender currency is associated with more risks around factors such as repayment and default.

When looking at the correlation between the remaining control variables and the overall loan interest rate (INTR), several observations can be made. Loan specific factors such as the term length ($TERM_{ln}$), the loan amount ($AMNT_{ln}$), and loan purpose (CAR, BUSI, SHORT) are all significantly related to the loan interest rate. All of the loan specific factors except the dummy variable indicating short-term loans have a negative correlation to the interest rate.

All of the control variables related to macroeconomic factors also exhibit a significant correlation to the interest rate. Factors such as the inflation rates ($INFL_{t-2}$), the unemployment rates (UNEMP), and the GDP growth (GDP_{t-4}) of borrower countries show positive correlation to the interest rates of the loans. It is of note that GDP growth (GDP_{t-4}) is related to higher interest rates as this is not very intuitive, as the inverse relation is observed in literature. This counterintuitive result may be due to lag misspecification of the GDP growth variable (GDP_{t-4}). Other macroeconomic variables such as the source region policy rate ($ECBR_{t-2}$), the borrower country stock performance ($STOCK_{t-4}$), the source region stock performance ($STX50_{t-4}$), the VIX, and geographical distance (DIST), show significant but very small relation to the interest rate.

The relation between GDP growth (GDP_{t-4}) and the unemployment rate (UNEMP) is virtually zero (-0.01***). Okun's Law, developed my Arthur Okun, states that generally, a 1% move in the GDP of a country is accompanied by an inverse change in the unemployment rate of 0.5% (Ball et al., 2017). Although a significant and negative relation is present in the correlation matrix, the magnitude of this relationship is economically insignificant. This may be due to specific underlying issues present in the countries investigated or due to the difference in lag structure used between the GDP growth rate and the unemployment rate measures.

Since GDP growth (GDP_{t-4}) exhibits relationships with variables such as the loan interest rate (INTR) and the unemployment rate (UNEMP) which contradict literature, it may be beneficial to test correlations using unlagged GDP growth values. When taking the unlagged GDP growth variable (GDP), there is a significant and positive relation present with both the interest rate (INTR) (0.4573***) and the unemployment rate (UNEMP) (0.1121***). For both relations, taking the unlagged values leads to more positive and economically significant correlations. While it is possible that there is a certain lag for which the relations turn negative, thus behaving as outlined in literature, it is possible that the underlying characteristics of the studied countries results in these contradictory results.

Table 11: Pearson Correlation Matrix

	INTR	AMNT	TERM	CAR	BUSI	SHORT	RISK	FXV	ECBR	INFL	UNEMP	GDP	STOCK	STX50	VIX	DIST
INTR	1.00															
AMNT	-0.16^{***}	1.00														
TERM	-0.08^{***}	0.68^{***}	1.00													
CAR	-0.06^{***}	0.27^{***}	0.25^{***}	1.00												
BUSI	-0.05^{***}	0.17^{***}	0.03^{***}	-0.01^{***}	1.00											
SHORT	0.13^{***}	-0.64^{***}	-0.83^{***}	-0.17^{***}	-0.05^{***}	1.00										
RISK	-0.41^{***}	0.53^{***}	0.50^{***}	0.32^{***}	0.11^{***}	-0.52^{***}	1.00									
FXV	0.37^{***}	-0.13^{***}	-0.06^{***}	-0.07^{***}	-0.08^{***}	0.18^{***}	-0.30^{***}	1.00								
ECBR	0.02^{***}	-0.37^{***}	-0.50^{***}	-0.01^{***}	-0.07^{***}	0.38^{***}	-0.27^{***}	-0.20^{***}	1.00							
INFL	0.20^{***}	-0.05^{***}	-0.01^{***}	-0.07^{***}	0.00^{**}	0.15^{***}	-0.19^{***}	-0.25^{***}	0.22^{***}	1.00						
UNEMP	0.27^{***}	-0.33^{***}	-0.21^{***}	0.30^{***}	-0.05^{***}	0.26^{***}	-0.43^{***}	0.19^{***}	0.16^{***}	-0.01^{***}	1.00					
GDP	0.32^{***}	-0.22^{***}	-0.31^{***}	0.02^{***}	-0.06^{***}	0.43^{***}	-0.44^{***}	0.21^{***}	0.25^{***}	0.34^{***}	-0.01^{***}	1.00				
STOCK	0.08^{***}	0.01^{***}	-0.07^{***}	-0.11^{***}	0.00	0.06^{***}	-0.03^{***}	0.06^{***}	0.09^{***}	0.05^{***}	-0.17^{***}	0.19^{***}	1.00			
STX50	0.04^{***}	0.05^{***}	0.03^{***}	0.04^{***}	0.01^{***}	-0.06^{***}	0.01^{***}	0.01^{***}	0.11^{***}	-0.21^{***}	0.02^{***}	0.01^{***}	0.33^{***}	1.00		
VIX	0.10^{***}	0.17^{***}	0.22^{***}	0.00	0.04^{***}	-0.19^{***}	0.14^{***}	-0.55^{***}	0.21^{***}	0.17^{***}	-0.12^{***}	-0.07^{***}	0.15^{***}	0.06^{***}	1.00	
DIST	0.10^{***}	-0.19^{***}	-0.06^{***}	0.06^{***}	-0.06^{***}	0.25^{***}	-0.05^{***}	-0.05^{***}	0.48^{***}	0.02^{***}	0.43^{***}	-0.05^{***}	-0.09^{***}	-0.03^{***}	0.05^{***}	1.00

* Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

** Variable transformations and lags: AMNT_{ln}, TERM_{ln}, ECBR_{t-2}, INFL_{t-2}, GDP_{t-4}, STOCK_{t-4}, STX50_{t-4}

4.3 Regression Results

This section presents the OLS regression results across five models, each focusing on a distinct set of explanatory variables: (I) loan-specific factors, (II) borrower-specific factors, (III) macroeconomic factors, (IV) a full model incorporating all variables, and (V) a full model excluding the short-term loan dummy (SHORT), which is highly correlated with loan term length ($\mathrm{TERM}_{\mathrm{ln}}$). Doing so allows for a clearer assessment of each group's individual and combined explanatory power. Across all models, the included variables are statistically significant at the 1% level ($p < 0.01$).

Loan-specific factors (I) by themselves only explain 3.64% of the variance in interest rates. Borrower-specific factors (II), which only include the Mintos risk score (RISK), explain 17.09% of variance in interest rates. The macroeconomic factor model (III) manages to explain 27.76% of the variance in interest rates. The full model (IV), which combines variables from all three models, is able to explain 31.80% of the variance in interest rates. When excluding the highly correlated short-term loan variable (V), the model explains 31.6% of variance in interest rates. While both the borrower factor model and the macroeconomic factor model hold quite a bit of explanatory power, the full model's explanatory power is only a slight improvement to the macroeconomic factor model. Interestingly, loan-specific factors hold very little explanatory power, meaning that most of the variance in interest rates come from the financial health of the loan originator, as well as their historical performance and cooperative structure. This relatively low explanatory power can also be seen in the difference in explained variance between model (IV) and (V), where removing short-term loans only decreases the adjusted R^2 value slightly. It is also important to note that although R^2 values and adjusted R^2 values appear identical, this is due to rounding. Adjusted R^2 values are marginally lower as the metric penalizes the addition of collinear explanatory variables.

The relationship between the Mintos risk score (RISK) and the expected loan interest rate shows a significant and negative relation (-2.3058***) in the borrower specific variable model. This relationship remains significant and negative (-0.9344***) in the full model but to a lesser magnitude. This suggests that parts of the effect of the Mintos risk score (RISK) are shared with other variables in the full model, such as certain macroeconomic factors or loan-specific factors. The regression shows that a standard deviation increase (0.63) in the Mintos risk score results in a 59 basis point decrease in the expected loan interest rate (calculated as: $-0.9344 \times 0.63 \approx -0.59$). This is consistent with findings from Hietala (2016), who found a 60 basis point reduction in the expected loan interest rate when a borrower's credit score rose by a standard deviation. Darmon et al. (2018) and Weiss et al. (2010) both showed directionally similar results with a standard deviation increase in the borrower credit score resulting in a 22 basis point and 860 basis point decrease in the expected loan interest rate, respectively.

The relationship between exchange rate volatility (FXV) and the expected loan interest rate shows a significant and positive relation (5.2206***) in the macroeconomic factors model. This relationship remains significant and positive (4.2943***) in the full model as well. The regression shows that a standard deviation increase (0.23) in the exchange rate volatility of a currency against the Euro pair, results in a 99 basis point increase in the expected interest rate of the loan (calculated as: $4.2943 \times 0.23 \approx 0.99$). While Delis et al. (2022) analyze the effect of a standard deviation increase in exchange rate volatility on loan spreads, the underlying impact of currency risk on borrowing costs remains similar. They find that a standard deviation increase in exchange rate volatility results in expected loan spreads that are 5.5 to 16.1 basis points higher (Delis et al., 2022). In contrast, this study shows a 99 basis point increase in the expected interest rates of cross-border P2P loans for a similar increase in volatility. Although direct comparison is not possible, the direction of the effects are consistent. The larger change may be due to differences in the risk profiles of traditional cross-border loans and P2P cross-border loans.

When added to the full model, variables related to loan types (CAR, BUSI, SHORT) experience a large swing in their coefficients. These values go from -0.6269*** to -2.1105***, from -1.2797*** to 0.7510***, from 1.1513*** to -0.6139***, for CAR, BUSI, and SHORT, respectively. These coefficient changes may be due to omitted variable bias or interaction effects between the loan purposes and some macroeconomic variables. Confounding or mediating factors that are not accounted for in the models may also serve as an explanation for the coefficient swings.

Table 12: Regression Results by Variable Group and Full Model

	(I)	(II)	(III)	(IV)	(V)
	LOAN FACTORS	**BORROWER FACTORS**	**MACRO FACTORS**	**FULL MODEL**	**EXCL SHORT**
$AMNT_{ln}$	-0.5383***			-0.0999***	-0.0792***
	(0.0052)			(0.0050)	(0.0049)
$TERM_{ln}$	0.3747***			0.2857***	0.4141***
	(0.0045)			(0.0039)	(0.0032)
CAR	0.6269***			-2.1105***	-2.2572***
	(0.0197)			(0.0244)	(0.0241)
BUSI	-1.2797***			0.7510***	0.6827***
	(0.0441)			(0.0475)	(0.0481)
SHORT	1.1513***			-0.6139***	
	(0.0144)			(0.0126)	
RISK		-2.3058***		-0.9344***	-0.8703***
		(0.0046)		(0.0071)	(0.0070)
FXV			5.2206***	4.2943***	4.4024***
			(0.0221)	(0.0215)	(0.0215)
$ECBR_{t-2}$			0.1315***	0.2538***	0.2726***
			(0.0038)	(0.0040)	(0.0040)
$INFL_{t-2}$			0.4206***	0.3382***	0.2909***
			(0.0089)	(0.0083)	(0.0081)
UNEMP			0.6200***	0.5709***	0.5854***
			(0.0017)	(0.0022)	(0.0022)
GDP_{t-4}			0.3087***	0.3331***	0.3135***
			(0.0017)	(0.0018)	(0.0017)
$STOCK_{t-4}$			0.4226***	0.3806***	0.3647***
			(0.0159)	(0.0150)	(0.0150)
$STX50_{t-4}$			-0.2678***	-0.1859***	-0.1812***
			(0.0174)	(0.0167)	(0.0167)
VIX			0.0885***	0.1010***	0.1053***
			(0.0011)	(0.0010)	(0.0010)
DIST			-0.0003***	-0.0002***	-0.0002***
			(0.0000)	(0.0000)	(0.0000)
Constant	15.5056	28.0660	5.7268	11.8324	10.7956***
	(0.0319)	(0.0298)	(0.0261)	(0.0657)	(0.0621)
Observations	727,812	727,812	727,812	727,812	717,812
R^2	0.0364	0.1709	0.2776	0.3180	0.3164
Adjusted R^2	0.0364	0.1709	0.2776	0.3180	0.3164

* Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

** R^2 and adjusted R^2 values are rounded; Adjusted R^2 is marginally lower

4.4 Robustness Checks

This section presents several robustness checks to ensure that the relationships discussed previously are valid across different scenarios. First, a year-by-year analysis is conducted to examine whether the relationships remain consistent over time. Next, a country-by-country analysis is conducted to examine whether the relationships remain consistent throughout different countries and economies. Finally, a median regression is carried out to identify any issues that may arise due to outliers in the data.

4.4.1 Year-by-Year Analysis

Table 13 shows the OLS regression results by year: 2022, 2023, and 2024. When looking at the adjusted R^2 values of the models, the 2022 model explains 44.05% of the variance in interest rates, the 2023 explains 57.92%, and the 2024 model explains 30.05%. It should be noted that the 2024 model has 598,347 samples, much more than the 2022 and 2023 models, which have 36,927 and 92,538 samples respectively. Although the number of loans in 2024 are more than six times greater than in 2023, the 2023 model indicates a much better fit when looking at adjusted R^2. This may indicate greater heterogeneity in the borrowers, contributing to a difficulty in risk pricing. The greater number of loans introduce a greater variety of loan originators, loan types, and macroeconomic factors, making it harder for the existing explanatory variables to explain variance in the loan interest rates. As the risk pricing mechanism is not public, this may also indicate a change in how this model sets interest rates internally, or diminished explanatory power of the included variables. The relation between the Mintos risk score (RISK) and the expected interest rate is much lower in 2024, when compared to the prior two years. This may indicate less weight given to this score internally when interest rates are set on Mintos. Appendix 2 includes the Pearson correlation matrices for 2022 (Table 19), 2023 (Table 20), and 2024 (Table 21). A majority of the correlations are significant at the 1% level ($p < 0.01$). The dependent variables, Mintos risk score (RISK) and exchange rate volatility (FXV), both show strong correlations to the interest rate of loans.

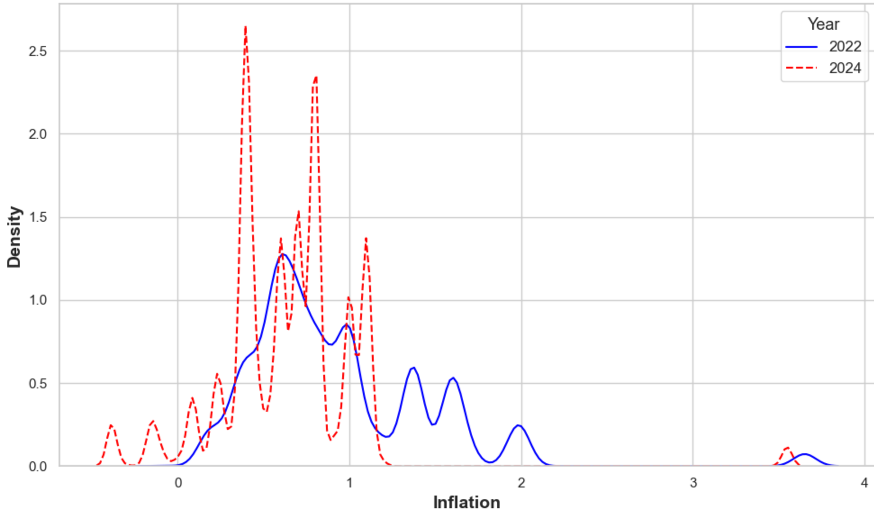
The Mintos risk score (RISK) is significant and negatively related to expected loan interest rates in all three years. This is in accordance with the overall full model, which showed a coefficient of -0.9344***. The coefficients in 2022 (-1.6695***) and 2023 (-1.5169***) are higher than in the overall full model but experience a decline in 2024 (-0.4134***).

Exchange rate volatility (FXV) is significant and positively related to expected loan interest rates in all three years. Again, this is in accordance with the full model, which had a coefficient of 4.2943***. The coefficient for exchange rate volatility (FXV) is much lower in 2022 (1.1719***) compared to 2023 (5.8492***) and 2024 (5.0622***).

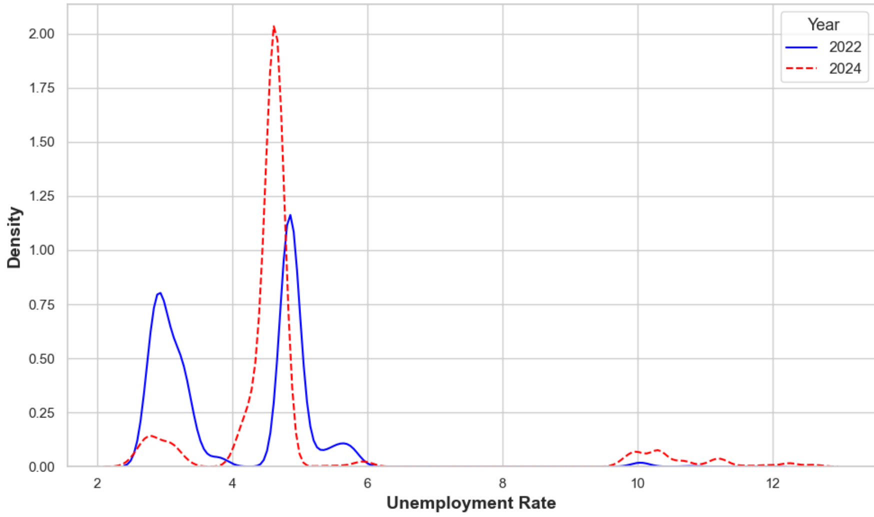
Although the overall results show that the direction and the significance of the relationships are consistent overtime, there are certain changes in coefficient magnitude that can be examined further. Some loan-specific factors, such as loan amounts (AMNT_{ln}), loan terms (TERM_{ln}), and loan types (CAR, SHORT), show fluctuations in coefficient magnitudes. Loan amounts (AMNT_{ln}) are positively related to expected loan interest rates in 2022 (0.0989***) and 2023 (0.0293***), but become negatively related to them in 2024 (-0.0633***). Although the economic significance of the variable is relatively small, it is of note. The effect size of the loan term (TERM_{ln}), shows a large fluctuation, ranging from 0.1353*** in 2024 to 0.8844**** in 2023. Car loans (CAR) and short-term loans (SHORT) experience spikes in their coefficients in 2024 and 2022, respectively.

Macroeconomic factors also experience fluctuations in their respective effect sizes. The ECB policy rate ($\text{ECBR}_{\text{t-2}}$) is omitted in 2022 as no policy rate changes were made during the period. In the following two years, however, the coefficient of the variable jumps from -0.0095 to 0.4318***. It should be noted that the ECB policy rate ($\text{ECBR}_{\text{t-2}}$) is not statistically related to the expected interest rate in 2023. Other macroeconomic factors, such as inflation ($\text{INFL}_{\text{t-2}}$), the unemployment rate (UNEMP), borrower and lender country stock market performance ($\text{STOCK}_{\text{t-4}}$ and $\text{STX50}_{\text{t-4}}$), and the VIX, show a certain degree of coefficient instability across years. The effect of inflation ($\text{INFL}_{\text{t-2}}$) is initially positively related (0.8269***) to the loan interest rates and experiences a decline in the following two years, ending with a negative relation (-0.0835***) in 2024. The unemployment rate (UNEMP) exhibits the reverse, beginning with a negative relation (-0.1020***), and increasing in the following two years, ending with a positive relation (0.7338***) in 2024. The lender country stock market performance ($\text{STX50}_{\text{t-4}}$) and the VIX also exhibit a similar evolution in effect size and see gradual positive growth in their coefficients over the three year period. A possible explanation for this gradual change may be related to how different factors are considered in the interest rate models of Mintos. It is possible that certain factors are added or removed from their models, or have their weights in the model changed. Kernel density plots for three of these variables ($\text{INFL}_{\text{t-2}}$,UNEMP,VIX) are shown in Figure 7. Although the kernel densities of inflation ($\text{INFL}_{\text{t-2}}$, Figure 7a) and unemployment (UNEMP, Figure 7b) show peaks around similar values in both 2022 and 2024, it can be seen that the distributions in 2022 are much wider. This larger variation may contribute to less precise and more volatile coefficient estimations. When looking at the kernel density of the VIX (Figure 7c), it is evident that 2022 was characterized by long period of elevated volatility, while 2024 was characterized by long periods of low volatility. This may explain why the effect of the VIX in 2024 on expected loan interest rates turns positive. As the period was mostly characterized by low volatility, a slight increase in the VIX is enough to have a large effect on expected loan interest rates.

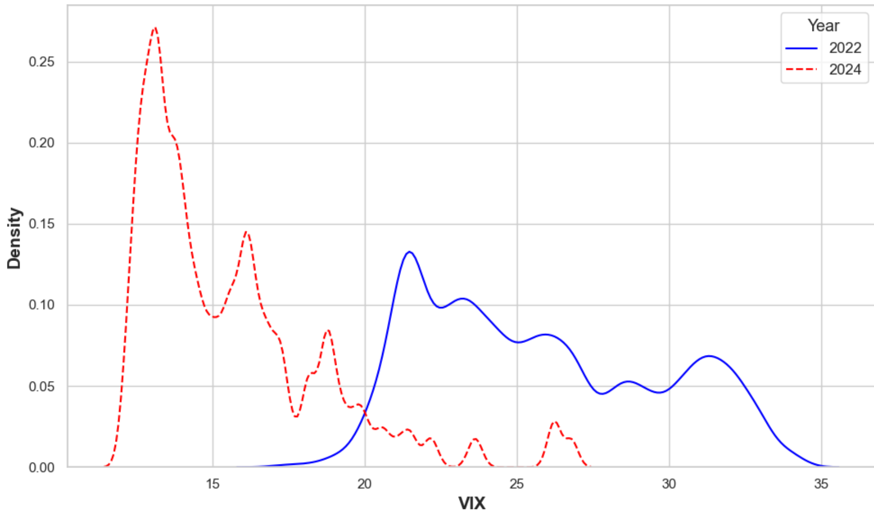
Overall, the year-by-year analysis shows robustness of the key relationships studied, especially when looking at the key predictors (RISK and FXV). However, certain variables exhibit fluctuations in their effect sizes which can be investigated further.



(a) Kernel Density Plot of $INFL_{t-2}$: 2022 vs 2024



(b) Kernel Density Plot of UNEMP: 2022 vs 2024



(c) Kernel Density Plot of VIX: 2022 vs 2024

Figure 7: Kernel Plots of Select Macroeconomic Variables

Table 13: Regression Results by Year

	(I)	(II)	(III)
	2022	**2023**	**2024**
$AMNT_{ln}$	0.0989^{***}	0.0293^{**}	-0.0633^{***}
	(0.0174)	(0.0129)	(0.0056)
$TERM_{ln}$	0.4798^{***}	0.8844^{***}	0.1353^{***}
	(0.0182)	(0.0108)	(0.0048)
CAR	-0.1307	-0.3908^{***}	-3.4287^{***}
	(0.1150)	(0.0484)	(0.0353)
BUSI	1.0073^{***}	1.2973^{***}	1.3849^{***}
	(0.0849)	(0.0898)	(0.0862)
SHORT	-3.1339^{***}	-0.2082^{***}	-0.6744^{***}
	(0.1992)	(0.0519)	(0.0141)
RISK	-1.6695^{***}	-1.5169^{***}	-0.4134^{***}
	(0.0357)	(0.0190)	(0.0098)
FXV	1.1719^{***}	5.8492^{***}	5.0622^{***}
	(0.0440)	(0.0585)	(0.0214)
$ECBR_{t-2}$	Omitted	-0.0095	0.4318^{***}
		(0.0118)	(0.0275)
$INFL_{t-2}$	0.8269^{***}	0.2566^{***}	-0.0835^{***}
	(0.0354)	(0.0293)	(0.0083)
UNEMP	-0.1020^{***}	0.3901^{***}	0.7338^{***}
	(0.0220)	(0.0112)	(0.0027)
GDP_{t-4}	0.5533^{***}	0.5299^{***}	0.3880^{***}
	(0.0139)	(0.0062)	(0.0022)
$STOCK_{t-4}$	0.5165^{***}	0.0438	0.5984^{***}
	(0.0691)	(0.0308)	(0.0172)
$STX50_{t-4}$	-1.1372^{***}	-0.3940^{***}	-0.1632^{***}
	(0.1026)	(0.0381)	(0.0195)
VIX	-0.0660^{***}	-0.0450^{***}	0.1703^{***}
	(0.0034)	(0.0042)	(0.0012)
DIST	0.0003^{***}	-0.0002^{***}	-0.0002^{***}
	(0.0000)	(0.0000)	(0.0000)
Constant	19.8867^{***}	16.1172^{***}	5.8597^{***}
	(0.3228)	(0.1994)	(0.1386)
Observations	36,927	92,538	598,347
R^2	0.4407	0.5793	0.3005
Adjusted R^2	0.4405	0.5792	0.3005

* Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.4.2 Country-by-Country Analysis

Table 15 shows the OLS regression results by country: Colombia, Kazakhstan, Kenya, Mexico, Poland, Romania, Uganda, and the United Kingdom. It should be noted that several variables are omitted from the regression as they stayed constant. These variables are all related to loan types (CAR, BUSI, SHORT) or the Mintos risk score (RISK), indicating that some countries only received loans for certain purposes, or that the loan originator in the country had a constant risk score. The adjusted R^2 values of each model can be assessed to determine the amount of explained variance in interest rates per country by the model. The model explains 72.68% of the variance in interest rates in Colombia, 19.50% of variance in Kazakhstan, 71.74% of variance in Kenya, 24.48% of variance in Mexico, 16.91% of variance in Poland, 27.07% of variance in Romania, 79.63% of variance in Uganda, and 71.68% of variance in the United Kingdom. Kazakhstan has the most loan origination (462,993) and represents over 63% of total loan origination.

The Mintos risk score (RISK) is statistically significant for all countries at the 1% level ($p < 0.01$), except in Colombia and Poland, where the variable is omitted. The Mintos risk score (RISK) is negatively related to expected loan interest rates in all countries except Kenya (0.4670***) and the United Kingdom (1.1317***). This is unexpected as less risky loans are receiving higher expected interest rate loans. In addition to this, the Mintos risk score's effect on expected interest rate is extremely negative in Uganda (-9.1092***). These variations can most likely be attributed to limited within-country variation of the Mintos risk score (RISK). As shown in Table 14, only two lending companies, both with a fixed risk score during the studied period, operated in Kenya. In Uganda, only one lending company operated during the studied period, with a risk score downgrade in August 2024. Similarly, in the United Kingdom, only one lending company was operational, with a risk score upgrade in August 2024.

The lack of variation in the Mintos risk score (RISK) within these three countries severely limits identification of a robust causal effect of the score on the expected loan interest rates. All other countries, besides the two omitted, have five or more risk scores associated with originated loans during the studied period. The limited within-country variation may lead to biased estimates where the coefficients may reflect omitted country-level confounders, rather than the effect of loan originator creditworthiness on the expected interest rates.

Table 14: Lending Companies and Risk Scores by Country

COUNTRY	LENDING COMPANY	PERIOD	RISK SCORE
Kenya	Mogo Kenya	Jan 2022 - Dec 2024	7.8
Kenya	Finclusion	Jan 2022 - Dec 2024	6.3
Uganda	Watu Credit Uganda	Jan 2022 - Aug 2024	7.1
Uganda	Watu Credit Uganda	Aug 2024 - Dec 2024	6.8
United Kingdom	Evergreen Finance	Jan 2022 - Aug 2024	6.6
United Kingdom	Evergreen Finance	Aug 2024 - Dec 2024	7.3

Exchange rate volatility (FXV) is statistically significant at the 1% level ($p < 0.01$) in all countries. However, this relation is only positive for Mexico (0.2210***), Romania (2.7332***), Uganda (5.7897***), and the United Kingdom (19.3808***). In Colombia, Kazakhstan, Kenya, and Poland, the relation is negative, with coefficients between exchange rate volatility (FXV) and the expected interest rate ranging from -1.1154 to -0.2025. Much like the key macroeconomic variables discussed in the previous section, Romania, Uganda, and the United Kingdom have exchange rate volatility (FXV) values that are very concentrated. During the research period of 2022 to 2024, Romania experienced a maximum exchange rate volatility spread of 0.38%. Uganda experienced a maximum exchange rate volatility spread of 0.55% and the United Kingdom experienced a maximum exchange rate volatility spread of 0.60%. As their currency volatilities are heavily concentrated, a small change in this value results in extremely large and unreliable changes in expected interest rates.

Table 15: Regression Results by Country

	COLOMBIA	KAZAKHSTAN	KENYA	MEXICO	POLAND	ROMANIA	UGANDA	UNITED KINGDOM
$AMNT_{ln}$	-0.0076***	-0.1073***	-0.0497***	-0.0984***	0.0394***	0.0463*	-0.5192***	-0.0483***
	(0.0006)	(0.0061)	(0.0093)	(0.0061)	(0.0110)	(0.0191)	(0.0788)	(0.0076)
$TERM_{ln}$	0.0133***	0.3675***	0.2340***	0.7247***	0.2200***	1.2144***	0.0658**	0.3218***
	(0.0021)	(0.0070)	(0.0113)	(0.0115)	(0.0129)	(0.0259)	(0.0244)	(0.0092)
CAR	Omitted	-1.9755***	-3.1977***	0.8239*	Omitted	3.7358***	Omitted	Omitted
		(0.0529)	(0.0826)	(0.3375)		(0.2237)		
BUSI	Omitted	Omitted	Omitted	2.5444***	Omitted	3.1912***	Omitted	Omitted
				(0.4944)		(0.1009)		
SHORT	0.0187***	-0.1968***	-0.7628***	2.0316***	Omitted	Omitted	Omitted	Omitted
	(0.0025)	(0.0175)	(0.0274)	(0.0310)				
RISK	Omitted	-0.8306***	0.4670***	-0.2308***	Omitted	-1.4944***	-9.1092***	1.1317***
		(0.0308)	(0.0430)	(0.0133)		(0.1487)	(0.1497)	(0.0409)
FXV	-0.2425***	-0.2815***	-1.1154***	0.2210***	-0.2025***	2.7332***	5.7897***	19.3808***
	(0.0155)	(0.0296)	(0.0553)	(0.0213)	(0.0317)	(0.2403)	(0.2657)	(0.1588)
$ECBR_{t\text{-}2}$	-0.5991***	-1.1793***	0.3531***	-0.2161***	-0.0058	0.2217***	-0.1850***	1.2001***
	(0.0220)	(0.0115)	(0.0117)	(0.0060)	(0.0073)	(0.0153)	(0.0233)	(0.0495)
$INFL_{t\text{-}2}$	0.0607***	0.2278***	-0.3613***	-0.3217***	0.8135***	-0.5485***	-0.6085***	0.1649***
	(0.0030)	(0.0097)	(0.0256)	(0.0226)	(0.0143)	(0.0332)	(0.0384)	(0.0188)
UNEMP	-0.0403***	-24.1625***	-1.4427***	-1.1251***	-0.0183	1.3998***	0.6774***	-2.7881***
	(0.0085)	(0.1075)	(0.0310)	(0.0282)	(0.0745)	(0.1056)	(0.0310)	(0.0657)
$GDP_{t\text{-}4}$	-0.1771***	-0.4289***	0.1879***	-0.2133***	-0.0551***	0.0452**	0.0882**	0.7691***
	(0.0083)	(0.0122)	(0.0088)	(0.0081)	(0.0058)	(0.0172)	(0.0357)	(0.1458)
$STOCK_{t\text{-}4}$	-0.0237***	0.3289***	0.2914***	-0.0615**	-0.1617***	0.7099***	0.5638***	-2.4356***
	(0.0029)	(0.0227)	(0.0242)	(0.0205)	(0.0189)	(0.0506)	(0.0808)	(0.0665)
$STX50_{t\text{-}4}$	0.0991***	-0.0733***	-0.0674*	0.1283***	0.1076***	-0.7688***	-1.2473***	1.0276***
	(0.0117)	(0.0231)	(0.0339)	(0.0229)	(0.0245)	(0.0454)	(0.0583)	(0.0407)
VIX	0.0058***	-0.0034*	0.1040***	0.0248***	0.0110***	0.0759***	0.0002	0.1531***
	(0.0002)	(0.0016)	(0.0027)	(0.0016)	(0.0022)	(0.0036)	(0.0053)	(0.0045)
DIST	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted
Constant	18.2581	138.5907	14.6273	13.6401	11.4583	8.8910	70.5504	3.2740
Observations	40,000	462,993	16,694	51,511	33,550	36,570	9,280	77,214
R^2	0.7286	0.1950	0.7176	0.2450	0.1693	0.2709	0.7965	0.7169
Adjusted R^2	0.7286	0.1950	0.7174	0.2448	0.1691	0.2707	0.7963	0.7168

* Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.4.3 Median Regression Analysis

As outliers were not processed prior to analysis due to possible loss of information, a median regression is carried out on the data (Table 18). Much like for the full regression, this is divided into five models: (I) loan-specific factors, (II) borrower-specific factors, (III) macroeconomic factors, (IV) a full model incorporating all variables, and (V) a full model excluding the short-term loan dummy (SHORT), which is highly correlated with loan term length ($TERM_{ln}$). Again, splitting the variables into distinct broad factors allows for clearer assessment of their individual and combined explanatory power. Across all models, the included variables are statistically significant at the 1% level ($p < 0.01$).

The full median regression (IV) reduces the sum of absolute errors by 24.09% compared to an intercept-only model, while model I reduces errors by 4.17%, model II reduces errors by 14.09%, model III reduces errors by 21.15%, and model V reduces errors by 23.83%. This means that model IV achieves a 24.09% improvement in predicting the median expected interest rate compared to using only the unconditional median. Comparing the median regression model to the OLS model is not straightforward as psuedo R^2 values cannot be compared to adjusted R^2 values. The OLS regression has an MSE (mean squared error) of 2.9108, while the median regression has an MAE (mean absolute error) of 2.1044. The MSE is only slightly higher than the MAE, indicating that no extreme outliers are largely skewing the predictions in the OLS model. As these two values are relatively close to one another, it is possible to conclude that the OLS model is not skewed by outliers and is robust to extreme variation.

The Mintos risk score (RISK) shows a roughly 11% decline between the OLS model (-0.9344***) and the median regression (-1.0366***). As the effect of the Mintos risk score (RISK) on the expected interest rate is larger in the median regression, it is possible to say that the creditworthiness of lending companies affects the typical loan to a greater extent than the average loan. The effect of the Mintos risk score (RISK), in both the OLS and the median regression model, is statistically and economically significant and negatively affects the expected loan interest rate.

Exchange rate volatility (FXV) increased by roughly 9% between the OLS model (4.2943***) and the median regression (4.6845***). Similar to the effect of the Mintos risk score (RISK), it is possible to say that exchange rate volatility (FXV) affects the expected interest rate of a typical loan to a greater extent than the average loan. In both the OLS and median regression models, the effect of exchange rate volatility (FXV) is statistically and economically significant and positively affects expected loan interest rates.

The coefficients of both, the Mintos risk score (RISK) and exchange rate volatility (FXV), can be examined at different quartiles (25th percentile, 50th percentile (median), 75th percentile) of the loan interest rate distribution. The coefficients for each dependent variable is shown in Table 17. Both the Mintos risk score (RISK) and exchange rate volatility (FXV) show a decreasing effect as one moves up the loan interest rate distribution. The effect of the Mintos risk score (RISK) decreases from -1.1965*** for the bottom 25% of loan interest rates to -0.7758*** for the top 25% of loan interest rates. Practically, this means that lower interest rate loans are more sensitive to the Mintos risk scores (RISK), as to protect already slim margins. The effect of exchange rate volatility (FXV) falls from 4.9333*** for the bottom 25% of loan interest rates to 3.4252*** for the top 25% of loan interest rates. Again, lower interest rate loans are more sensitive to the effects of exchange rate volatility (FXV), possibly to protect the slimmer margins. It may also be that lower interest rate loans are less sensitive to macroeconomic risk.

Table 16: Quantile Regression Coefficients for Mintos Risk Score and Exchange Rate Volatility

VARIABLE	25TH PERCENTILE	MEDIAN	75TH PERCENTILE
Mintos Risk Score (RISK)	-1.1965***	-1.0366***	-0.7758***
Exchange Rate Volatility (FXV)	4.9333***	4.6845***	3.4252***

* Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

When comparing the OLS model to the median regression model, several coefficients can be further investigated. The effect of inflation ($INFL_{t-2}$) flips from 0.3382*** in the OLS model to -0.1490*** in the median regression model. The effect of the STOXX50 performance ($STX50_{t-4}$) also flips from -0.1859*** in the OLS model to 1.0904*** in the median regression. Much like for the dependent variables, the coefficients of inflation ($INFL_{t-2}$) and the STOXX50 ($STX50_{t-4}$) performance can be analyzed at different quartiles to investigate how they affect expected loan interest rates along the distribution.

Table 17: Quantile Regression Coefficients for Inflation and STOXX50 Performance

VARIABLE	25TH PERCENTILE	MEDIAN	75TH PERCENTILE
Inflation ($INFL_{t-2}$)	-0.2374***	-0.1490***	0.3220***
STOXX50 Performance ($STX50_{t-4}$)	-0.2588***	1.0904***	0.0623***

* Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The effect of inflation ($INFL_{t-2}$) gradually increases as one moves up the distribution of loan interest rates, starting at a coefficient of -0.2374*** for the bottom 25% of loan rates and ending with a coefficient of 0.3220*** for the top 25% of loan rates. On the other hand, STOXX50 performance ($STX50_{t-4}$) has a negative effect (-0.2588***) on expected loan interest rates for the bottom 25% of loan rates, a very large positive effect (1.0904***) on expected loan interest rates for the median loan interest rates, and a slight positive effect (0.0623***) on the expected interest rates of the top 25% of loan rates.

Table 18: Median Regression Results by Variable Group and Full Model

	(I)	(II)	(III)	(IV)	(V)
	LOAN FACTORS	**BORROWER FACTORS**	**MACRO FACTORS**	**FULL MODEL**	**EXCL SHORT**
$AMNT_{ln}$	-0.5289***			-0.0919***	-0.0610***
	(0.0040)			(0.0050)	(0.0050)
$TERM_{ln}$	0.0437***			0.2203***	0.4089***
	(0.0040)			(0.0040)	(0.0030)
CAR	0.2521***			-2.4081***	-2.5942***
	(0.0200)			(0.0300)	(0.0320)
BUSI	-1.7172***			0.4528***	0.3819***
	(0.0670)			(0.0740)	(0.0800)
SHORT	0.7223***			-0.9610***	
	(0.0120)			(0.0150)	
RISK		-2.0685***		-1.0366***	-0.9691***
		(0.0020)		(0.0100)	(0.0110)
FXV			5.5303***	4.6845***	4.3025***
			(0.0140)	(0.0210)	(0.0220)
$ECBR_{t-2}$			0.2403***	0.2935***	0.2931***
			(0.0030)	(0.0040)	(0.0050)
$INFL_{t-2}$			0.0723***	-0.1490***	-0.1544***
			(0.0070)	(0.0090)	(0.0100)
UNEMP			0.6543***	0.6022***	0.6045***
			(0.0020)	(0.0030)	(0.0040)
GDP_{t-4}			0.1600***	0.1943***	0.2066***
			(0.0010)	(0.0020)	(0.0020)
$STOCK_{t-4}$			0.5320***	0.6694***	0.5354***
			(0.0100)	(0.0150)	(0.0160)
$STX50_{t-4}$			1.0823***	1.0904***	1.1472***
			(0.0120)	(0.0170)	(0.0190)
VIX			0.1323***	0.1711***	0.1566***
			(0.0010)	(0.0010)	(0.0010)
DIST			-0.0003***	-0.0002***	-0.0002***
			(0.0000)	(0.0000)	(0.0000)
Constant	16.3309***	26.8040***	4.8223***	11.4156***	10.5704***
	(0.0250)	(0.0140)	(0.0200)	(0.0890)	(0.0930)
Observations	727,812	727,812	727,812	727,812	727,812
Pseudo R^2	0.0417	0.1409	0.2115	0.2409	0.2383

* Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5 Conclusion and Discussions

This study examined the effects of exchange rate volatility and the Mintos risk score on the expected interest rates of cross-border P2P loans through the use of a multiple linear regression. A sample of 727,812 loans during the three year period from 2022 to 2024 from eight different countries was used to investigate this effect.

The analysis showed that both exchange rate volatility and the Mintos risk score are statistically and economically related to the overall interest rates received by lenders on Mintos. High exchange rate volatility between the lender currency and the borrower currency significantly increased expected loan interest rates. In addition to this, increases in the Mintos risk score, indicating less risky loan originators and thus more creditworthy borrowers, reduced loan interest rates significantly. Borrower-specific factors, considered to be solely the Mintos risk score, and certain macroeconomic factors, explain a majority of the variance in expected interest rates. On the other hand, loan-specific factors contributed only marginally to the expected interest rates.

In addition to the variables of interest, it was also found that the unemployment rate of the borrower country, the stock index performance of the borrower country, and the stock index performance of the lender country had a significant economic effect on the expected interest rates of loans on the platform. Loan purpose also showed large variations in expected loan interest rates with car loans receiving the lowest expected interest rate relative to personal loans. Overall, the model was able to explain around 32% of the variance in P2P cross-border interest rates on Mintos.

Robustness of the findings was investigated through a year-by-year analysis, a country-by-country analysis, and a median regression to mitigate extreme outlier effects. These robustness checks showed that the underlying relationships hold under different circumstances. As such, the effects of the Mintos risk score and exchange rate volatility on the expected loan interest rate in cross-border P2P lending on Mintos are robust.

The findings highlight the importance of strict risk assessment at the loan originator level, as Mintos does not disclose individual borrower-level data. Additionally, this paper provides one of the first studies on the outsized impact of exchange rate volatility on P2P cross-border lending rates.

6 Limitations and Future Research

Several limitations are present in the study. First off, as granular level borrower data is not disclosed on Mintos, lenders must rely on the Mintos risk score to inform their lending decisions. As Mintos packages individual loans into note offerings with multiple underlying loans, traditional borrower specific factors such as their debt-to-income ratio, homeownership status, and marital status, are not readily available. Mintos combats this by assigning a risk score to borrower country loan originators, who are tasked with packaging these notes, based on factors such as their financial status and legal structure. The Mintos risk score is determined on several factors that may require some self-reporting from the lending companies. As such, the incentives for lending companies to properly disclose their financial situation are lacking. If a lending company is not financially healthy, it is not in their best interest to disclose this fully to Mintos as this will be reflected in their risk score in the form of a downgrade. Additionally, as Mintos' main revenue driver is in the form of platform fees, generating a maximum amount of volume is in their best interest. It is possible that lenders may not receive full and proper disclosure about risks from both the lending company and Mintos, leading to possible cases of information asymmetry. As such, the Mintos risk score may not be the best proxy for borrower creditworthiness.

Additionally, there is limited within-country variation of the Mintos risk score. As highlighted in the robustness checks, some lending companies are only assigned one or two risk scores. This leads to some unreliable coefficient values that have been discussed in detail during the robustness analysis.

The model may also not capture all relevant factors that influence interest rates on Mintos. Changes in the risk pricing model used by Mintos over time are not capture in the model as this is not publicly disclosed. Unobserved country-specific regulatory variables are also omitted due to the complexity of finding a quantitative proxy for such a factor. Several macroeconomic variables were considered to have lagged effects and although this was based on available literature, they may degrade the model's explanatory power.

Further studies should be carried out using granular borrower-level data if available. Doing so would enable analysis on how borrower-level data interacts with lending company data, and provide a more complete analysis of the complex dynamics behind pricing cross-border P2P loans. Additionally, looking at loan spreads instead of absolute interest rates would allow the research to be more aligned with traditional finance research and isolate the risk premium of P2P lending more completely.

Carrying out the same study across different platforms would also allow for more reliable reasoning for how certain factors impact the expected interest rates of P2P loans. Similar research could also be carried out on a platform that utilizes a reverse-auction mechanism for setting interest rates, rather than a posted-price mechanism, to determine to what extent macroeconomic risks are considered by purely lenders, rather than an internal risk model. Proxies for risk appetite that are more aligned with retail lenders, rather than the VIX, could also be included as a variable in order to capture this dynamic.

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7 Appendices

7.1 Appendix 1: Assumptions Testing

7.1.1 White's Test for Homoskedasticity of Residuals

TEST	CHI-SQUARE	DF	P-VALUE
White	109,005.99	129	<0.0001

7.1.2 Jarque-Bera Test for Normality of Residuals

TEST	STATISTIC	P-VALUE
Jarque-Bera	180,000	<0.0001

7.1.3 Variance Inflation Factor (VIF) for Multicollinearity

VARIABLE	VIF
$TERM_{ln}$	4.77
SHORT	4.64
RISK	3.42
UNEMP	2.93
$AMNT_{ln}$	2.33
DIST	2.28
$ECBR_{t\text{-}2}$	2.20
CAR	2.07
$GDP_{t\text{-}4}$	2.03
FXV	1.91
VIX	1.54
$INFL_{t\text{-}2}$	1.44
$STOCK_{t\text{-}4}$	1.29
$STX50_{t\text{-}4}$	1.25
BUSI	1.06
Mean VIF	2.34

7.2 Appendix 2: Pearson Correlation Matrices by Year

7.2.1 Pearson Correlation Matrix for 2022

Table 19

	INTR	AMNT	TERM	CAR	BUSI	SHORT	RISK	FXV	ECBR	INFL	UNEMP	GDP	STOCK	STX50	VIX	DIST
INTR	1.00															
AMNT	-0.11^{***}	1.00														
TERM	0.07^{***}	-0.24^{***}	1.00													
CAR	-0.09^{***}	0.19^{***}	0.01^{***}	1.00												
BUSI	-0.11^{***}	0.37^{***}	-0.17^{***}	-0.02^{***}	1.00											
SHORT	-0.03^{***}	-0.01^{***}	-0.01^{***}	-0.01^{***}	-0.01^{***}	1.00										
RISK	-0.51^{***}	0.16^{***}	0.12^{***}	0.19^{***}	0.14^{***}	-0.11^{***}	1.00									
FXV	0.34^{***}	0.05^{***}	-0.20^{***}	-0.08^{***}	-0.17^{***}	0.00	-0.38^{***}	1.00								
ECBR	-	-	-	-	-	-	-	-	-							
INFL	0.38^{***}	-0.08^{***}	-0.09^{***}	0.01^{**}	-0.03^{***}	-0.02^{***}	-0.31^{***}	0.05^{***}	-	1.00						
UNEMP	0.41^{***}	-0.12^{***}	-0.06^{***}	0.22^{***}	-0.13^{***}	0.15^{***}	-0.51^{***}	0.51^{***}	-	0.25^{***}	1.00					
GDP	0.55^{***}	-0.17^{***}	0.03^{***}	0.05^{***}	-0.10^{***}	0.01	-0.63^{***}	0.23^{***}	-	0.54^{***}	0.46^{***}	1.00				
STOCK	0.06^{***}	-0.01^{*}	-0.08^{***}	-0.01^{***}	0.01	-0.01^{*}	-0.01	0.09^{***}	-	0.26^{***}	0.15^{***}	-0.04^{***}	1.00			
STX50	-0.03^{***}	0.01^{**}	-0.03^{***}	0.07^{***}	0.00	0.00	-0.01^{***}	0.11^{***}	-	-0.05^{***}	0.10^{***}	-0.03^{***}	0.31^{***}	1.00		
VIX	-0.11^{***}	0.05^{***}	-0.05^{***}	-0.03^{***}	0.02^{***}	0.02^{***}	0.10^{***}	0.11^{***}	-	0.00	0.02^{***}	-0.14^{***}	0.15^{***}	-0.12^{***}	1.00	
DIST	-0.11^{***}	-0.02^{***}	0.23^{***}	-0.02^{***}	-0.13^{***}	0.05^{***}	0.58^{***}	0.15^{***}	-	-0.15^{***}	0.12^{***}	-0.36^{***}	0.11^{***}	0.02^{**}	0.13^{***}	1.00

* Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
** Variable transformations and lags: AMNT_{ln}, TERM_{ln}, ECBR_{t-2}, INFL_{t-2}, GDP_{t-4}, STOCK_{t-4}, STX50_{t-4}
*** ECBR_{t-2} is omitted as the value stayed constant throughout 2022

7.2.2 Pearson Correlation Matrix for 2023

Table 20

	INTR	AMNT	TERM	CAR	BUSI	SHORT	RISK	FXV	ECBR	INFL	UNEMP	GDP	STOCK	STX50	VIX	DIST
INTR	1.00															
AMNT	-0.13^{***}	1.00														
TERM	0.14^{***}	0.13^{***}	1.00													
CAR	-0.15^{***}	0.29^{***}	0.00	1.00												
BUSI	-0.07^{***}	0.25^{***}	-0.10^{***}	-0.02^{***}	1.00											
SHORT	0.01^{***}	-0.24^{***}	-0.47^{***}	-0.05^{***}	-0.02^{***}	1.00										
RISK	-0.59^{***}	0.27^{***}	0.05^{***}	0.35^{***}	0.09^{***}	-0.17^{***}	1.00									
FXV	0.50^{***}	-0.05^{***}	0.10^{***}	-0.13^{***}	-0.12^{***}	0.04^{***}	-0.18^{***}	1.00								
ECBR	-0.16^{***}	-0.01^{*}	-0.19^{***}	0.13^{***}	0.00	0.19^{***}	0.03^{***}	-0.16^{***}	1.00							
INFL	0.44^{***}	-0.06^{***}	0.04^{***}	-0.07^{***}	-0.01^{**}	-0.14^{***}	-0.45^{***}	0.22^{***}	-0.45^{***}	1.00						
UNEMP	0.49^{***}	-0.22^{***}	-0.18^{***}	0.22^{***}	-0.06^{***}	0.31^{***}	-0.50^{***}	0.41^{***}	0.05^{***}	0.28^{***}	1.00					
GDP	0.52^{***}	-0.09^{***}	-0.12^{***}	0.02^{***}	-0.03^{***}	0.08^{***}	-0.34^{***}	0.45^{***}	-0.32^{***}	0.47^{***}	0.61^{***}	1.00				
STOCK	0.03^{***}	0.05^{***}	0.01^{***}	-0.07^{***}	0.00	-0.05^{***}	0.00	0.16^{***}	0.08^{***}	-0.14^{***}	-0.06^{***}	-0.06^{***}	1.00			
STX50	-0.03^{***}	0.02^{***}	0.01^{***}	0.04^{***}	0.01^{**}	0.00	-0.01^{***}	-0.03^{***}	0.18^{***}	-0.16^{***}	0.02^{***}	-0.05^{***}	0.52^{***}	1.00		
VIX	0.11^{***}	0.03^{***}	0.19^{***}	-0.09^{***}	0.00	-0.15^{***}	0.01^{**}	0.15^{***}	-0.69^{***}	0.37^{***}	-0.09^{***}	0.23^{***}	-0.02^{***}	0.04^{***}	1.00	
DIST	-0.07^{***}	0.04^{***}	0.07^{***}	0.02^{***}	-0.07^{***}	0.09^{***}	0.46^{***}	0.55^{***}	-0.06^{***}	-0.34^{***}	0.12^{***}	0.13^{***}	0.00	-0.08^{***}	0.02^{***}	1.00

* Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

** Variable transformations and lags: AMNT_{ln}, TERM_{ln}, ECBR_{t-2}, INFL_{t-2}, GDP_{t-4}, STOCK_{t-4}, STX50_{t-4}

7.2.3 Pearson Correlation Matrix for 2024

Table 21

	INTR	AMNT	TERM	CAR	BUSI	SHORT	RISK	FXV	ECBR	INFL	UNEMP	GDP	STOCK	STX50	VIX	DIST
INTR	1.00															
AMNT	-0.17^{***}	1.00														
TERM	-0.09^{***}	0.66^{***}	1.00													
CAR	-0.03^{***}	0.28^{***}	0.32^{***}	1.00												
BUSI	-0.03^{***}	0.12^{***}	0.03^{***}	-0.01^{***}	1.00											
SHORT	0.14^{***}	-0.60^{***}	-0.81^{***}	-0.19^{***}	-0.04^{***}	1.00										
RISK	-0.37^{***}	0.54^{***}	0.51^{***}	0.32^{***}	0.10^{***}	-0.55^{***}	1.00									
FXV	0.38^{***}	-0.26^{***}	-0.21^{***}	-0.06^{***}	-0.07^{***}	0.31^{***}	-0.43^{***}	1.00								
ECBR	0.00^{***}	-0.08^{***}	-0.08^{***}	-0.01^{***}	-0.02^{***}	0.04^{***}	-0.04^{***}	-0.17^{***}	1.00							
INFL	0.16^{***}	-0.17^{***}	-0.19^{***}	-0.09^{***}	-0.01^{***}	0.32^{***}	-0.24^{***}	0.21^{***}	0.02^{***}	1.00						
UNEMP	0.24^{***}	-0.28^{***}	-0.10^{***}	0.36^{***}	-0.03^{***}	0.18^{***}	-0.39^{***}	0.16^{***}	-0.01^{***}	0.01^{***}	1.00					
GDP	0.29^{***}	-0.12^{***}	-0.20^{***}	0.04^{***}	-0.04^{***}	0.38^{***}	-0.40^{***}	0.31^{***}	0.07^{***}	0.42^{***}	-0.15^{***}	1.00				
STOCK	0.10^{***}	0.06^{***}	-0.02^{***}	-0.12^{***}	0.01^{***}	0.03^{***}	0.00	0.08^{***}	-0.05^{***}	0.12^{***}	-0.26^{***}	0.24^{***}	1.00			
STX50	0.06^{***}	0.08^{***}	0.06^{***}	0.05^{***}	0.01^{***}	-0.09^{***}	0.03^{***}	0.15^{***}	-0.32^{***}	-0.24^{***}	0.01^{***}	0.01^{***}	0.25^{***}	1.00		
VIX	0.18^{***}	0.01^{***}	0.00^{*}	0.02^{***}	0.00	-0.04^{***}	0.01^{***}	0.12^{***}	0.11^{***}	0.07^{***}	-0.06^{***}	0.04^{***}	0.25^{***}	0.07^{***}	1.00	
DIST	0.17^{***}	-0.29^{***}	-0.13^{***}	0.08^{***}	-0.04^{***}	0.34^{***}	-0.32^{***}	0.52^{***}	-0.05^{***}	0.11^{***}	0.53^{***}	-0.05^{***}	-0.15^{***}	-0.02^{***}	0.02^{***}	1.00

* Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

** Variable transformations and lags: AMNT_{ln}, TERM_{ln}, ECBR_{t-2}, INFL_{t-2}, GDP_{t-4}, STOCK_{t-4}, STX50_{t-4}