UNIVERSITY OF LJUBLJANA
SCHOOL OF ECONOMICS AND BUSINESS

MASTER'S THESIS

EVALUATING THE IMPACT OF TRADE CREDIT INSURANCE ON LIQUIDITY AND PAYMENT DEFAULT RISK AMONG SMALL AND MEDIUM-SIZED ENTERPRISES: A CASE OF COFACE SLOVENIA

Ljubljana, July 2026 Anja Ilić

AUTHORSHIP STATEMENT

The undersigned Anja Ilić, a student at the University of Ljubljana, School of Economics and Business, (hereafter: UL SEB), author of this written final work of studies with the title Evaluating the impact of trade credit insurance on liquidity and payment default risk among small and medium-sized enterprises: The case of Coface Slovenia, prepared in collaboration with mentor Denis Marinšek.

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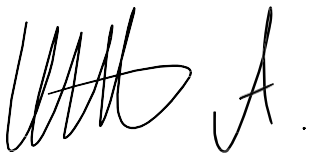
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ABSTRACT

This master's thesis examines the relationship between trade credit insurance, liquidity, and payment default risk among small and medium-sized enterprises (hereinafter: SMEs) in Slovenia. The study uses firm-level data from Coface Slovenia for the period 2022–2024. Liquidity is measured using the cash ratio, current ratio, quick ratio, and net working capital to total assets, while payment default risk is assessed through days sales outstanding and blocked-account incidence. The empirical analysis applies descriptive statistics, hypothesis testing, and regression models, controlling for firm size and industry sector. The results show that insured SMEs generally display more favourable financial characteristics than non-insured SMEs. Trade credit insurance is positively associated with broader liquidity measures, particularly the current ratio and net working capital to total assets. The evidence is stronger for payment default risk, as insured SMEs have lower days sales outstanding and a significantly lower incidence of account blockage. The findings suggest that trade credit insurance is associated with more favourable financial outcomes among Slovenian SMEs, especially through more efficient receivables collection and lower exposure to account blockage.

KEY WORDS: trade credit insurance, small and medium-sized enterprises, liquidity, payment default risk, receivables management, Slovenia

SUSTAINABLE DEVELOPMENT GOALS



POVZETEK

Magistrsko delo preučuje povezavo med zavarovanjem terjatev, likvidnostjo in tveganjem neplačila pri malih in srednje velikih podjetjih (v nadaljevanju: MSP) v Sloveniji. V študiji uporabljam podatke družbe Coface Slovenija za obdobje 2022–2024. Likvidnost merim z denarnim količnikom, kratkoročnim koeficientom, pospešenim koeficientom in razmerjem med neto obratnim kapitalom in celotnimi sredstvi, medtem ko tveganje neplačila ocenjujem s pomočjo kazalnika dni vezave terjatev in pojavnosti blokade računov. V empirični analizi predstavim opisno statistiko, statistično preverjanje domnev in regresijske modele. Rezultati kažejo, da imajo zavarovana MSP na splošno ugodnejše finančne značilnosti kot nezavarovana MSP. Zavarovanje terjatev je pozitivno povezano s širšimi kazalniki likvidnosti, zlasti s kratkoročnim koeficientom ter razmerjem med neto obratnim kapitalom in celotnimi sredstvi. Dokazi so močnejši pri tveganju neplačila, saj imajo zavarovana MSP krajše obdobje vezave terjatev in bistveno nižjo pojavnost blokade računov. Ugotovitve kažejo, da je zavarovanje terjatev povezano z ugodnejšimi finančnimi rezultati slovenskih MSP, zlasti prek učinkovitejšega upravljanja terjatev in manjše izpostavljenosti blokadi računov.

KLJUČNE BESEDE: zavarovanje terjatev, mala in srednje velika podjetja, likvidnost, tveganje plačilne neizpolnitve, upravljanje terjatev, Slovenija

CILJI TRAJNOSTNEGA RAZVOJA



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LIST OF ABBREVIATIONS

sl. – Slovene

AJPES – (sl. Agencija Republike Slovenije za javnopravne evidence in storitve); Agency of the Republic of Slovenia for Public Legal Records and Related Services

AUC – Area Under the Curve

B2B – Business-to-Business

CEE – Central and Eastern Europe

CI – Confidence Interval

DSO – Days Sales Outstanding

EIB – European Investment Bank

EISMEA – European Innovation Council and SMEs Executive Agency

EU – European Union

ICISA – International Credit Insurance & Surety Association

NWC/TA – Net Working Capital to Total Assets

OLS – Ordinary Least Squares

SMEs – (sl. mala in srednje velika podjetja); Small and Medium-Sized Enterprises

TCI – (sl. zavarovanje terjatev); Trade Credit Insurance

1 INTRODUCTION

Small and medium-sized enterprises (hereinafter: SMEs) represent a central part of the Slovenian and European economy. They account for the overwhelming majority of enterprises, generate a substantial share of employment and business revenues, and play an important role in economic growth, innovation, and regional development. At the same time, SMEs are more financially vulnerable than large enterprises because they usually have more limited internal financial buffers, weaker bargaining power with banks, and greater dependence on timely cash inflows from customers. Their ability to maintain liquidity therefore depends not only on access to external finance, but also on the timely collection of trade receivables.

This issue is particularly relevant in the context of late payments and buyer non-payment. In business-to-business (hereinafter: B2B) transactions, suppliers often sell goods and services on deferred payment terms, which means that sales are recorded before cash is received. While trade credit can support business growth and customer relationships, it also exposes suppliers to liquidity pressure and payment default risk. For SMEs, delayed collection of receivables may create difficulties in meeting short-term obligations, financing daily operations, or pursuing investment opportunities. Previous research and policy reports show that late payments remain an important constraint on SME liquidity, financial stability, and business continuity, particularly in periods of economic uncertainty (Ferrara & Ferraresi, 2022).

Trade credit insurance (hereinafter: TCI) is one of the instruments used to manage these risks. TCI protects enterprises against losses arising from buyer insolvency or protracted default and is therefore directly linked to the management of trade receivables. However, its role is broader than indemnification alone. Through buyer assessment, credit-limit decisions, monitoring, and debt collection support, TCI may also influence firms' customer-risk management and receivables collection practices (Becue, 2013; Jus, 2004). This makes TCI particularly relevant for SMEs, which often lack the internal resources needed to conduct comprehensive credit risk monitoring on their own.

Existing literature provides a well-developed theoretical explanation of the mechanisms of TCI and its role in protecting trade receivables. Recent research also links credit insurance to payment-risk mitigation and liquidity-related channels. For example, Li et al. (2016) emphasise that suppliers offering deferred payment terms may face non-payment risk and capital constraints simultaneously, while Ji et al. (2026) identify liquidity relief and payment-risk mitigation as important channels through which export credit insurance can affect firm outcomes. However, limited empirical attention has been paid to whether SMEs with TCI coverage differ from non-insured SMEs in firm-level liquidity and payment default risk indicators. This gap is particularly relevant in Slovenia, where SMEs play a central role in the economy and where late payments and insolvency risk remain important challenges for business stability.

The purpose of this master's thesis is therefore to examine whether SMEs covered by TCI differ from non-insured SMEs with respect to liquidity and payment default risk in Slovenia. The thesis focuses on a case study of Coface Slovenia and uses firm-level data for the period 2022–2024. The central research question guiding the analysis is: How is trade credit insurance associated with liquidity and payment default risk among Slovenian SMEs? To address this question, the thesis examines two related dimensions of SME financial resilience. The first concerns liquidity, measured through accounting-based liquidity indicators, while the second concerns payment default risk, measured through receivables collection efficiency and blocked-account incidence. Accordingly, the following two hypotheses are developed and tested:

H1: SMEs covered by TCI exhibit stronger liquidity than non-insured SMEs.

H2: SMEs covered by TCI exhibit lower payment default risk than non-insured SMEs, as reflected in more efficient receivables collection and a lower incidence of account blockage.

The empirical analysis uses a quantitative firm-level approach. The final sample consists of 395 Slovenian SMEs, including 238 insured and 157 non-insured SMEs. Liquidity is measured using the cash ratio, current ratio, quick ratio, and net working capital to total assets (hereinafter: NWC/TA), while payment default risk is assessed using days sales outstanding (hereinafter: DSO) and blocked-account incidence. The analysis proceeds through descriptive statistics, hypothesis testing, and regression models. In the regression analysis, insurance status is used as the key explanatory variable, while liquidity and payment default risk indicators are modelled as dependent variables. OLS regression models are estimated for the continuous dependent variables, namely the liquidity indicators and DSO, while logistic regression is applied to blocked-account incidence as a binary outcome. The models control for firm size category and industry sector. Since the dataset is observational, the results are interpreted as evidence of association rather than causal effects.

The contribution of this thesis is twofold. First, it provides firm-level empirical evidence on whether SMEs covered by TCI differ from non-insured SMEs in terms of liquidity and payment default risk in the Slovenian context, where this relationship has received limited empirical attention. Second, it distinguishes between liquidity outcomes and payment default risk indicators, allowing a more nuanced understanding of the channels through which TCI may be associated with SME financial resilience. Rather than treating TCI as a general liquidity solution, the thesis examines whether its relevance is more clearly visible through receivables collection efficiency and reduced exposure to account blockage.

The thesis is structured as follows. The first part presents the role of SMEs in the Slovenian economy, including their definition, economic significance, financing constraints, and exposure to late payments. The second part explains the concept and mechanisms of TCI, including risk types, policy structures, credit-limit decisions, debt collection, and the strategic and operational benefits of TCI for SMEs. The third part introduces Coface Group and Coface Slovenia, with a focus on Coface Slovenia's role in the Slovenian credit insurance market and its product

portfolio. The fourth part presents the empirical research design, including the hypotheses, dataset, variable definitions, methodology, and empirical strategy. The results section then presents descriptive statistics, hypothesis testing, and regression findings. The discussion interprets the results for liquidity and payment default risk, outlines theoretical and practical implications, and addresses the main limitations of the study together with directions for future research. The thesis concludes by summarising the key findings and their relevance for understanding the role of TCI in SME financial resilience.

2 THE ROLE OF SMEs IN THE SLOVENIAN ECONOMY

This chapter provides the contextual basis for analysing the financial position of SMEs in Slovenia. It first defines SMEs according to the EU classification, then explains their economic significance, and finally discusses the main financial challenges they face, particularly access to finance and payment behaviour.

2.1 Definition and classification of SMEs

Within the European Union (hereinafter: EU), the definition of SMEs is standardised through Commission Recommendation 2003/361/EC, which provides a common classification framework across all Member States. According to this recommendation, enterprises are classified into three main categories based on the number of employees and either their annual turnover or balance sheet total (European Commission, n.d.).

A micro enterprise employs fewer than ten persons and has an annual turnover or balance sheet total not exceeding €2 million. A small enterprise employs fewer than 50 persons and has an annual turnover or balance sheet total not exceeding €10 million**.** Finally, a medium-sized enterprise is defined as one that employs fewer than 250 persons and generates an annual turnover of up to €50 million or has a balance sheet total not exceeding €43 million (European Commission, n.d.). This harmonised classification supports cross-country comparability and provides the basis for various European initiatives targeting SMEs, including financial support programmes, regulatory simplifications, and improved access to funding (European Commission, n.d.).

The EU framework is consistently applied in Slovenia, where SMEs account for the vast majority of all registered enterprises (Government of the Republic of Slovenia, n.d.). Applying the EU definition ensures analytical consistency, enables cross-country comparisons, and facilitates the integration of Slovenia's SME sector into broader European policy discussions. For the purposes of this master's thesis, the EU classification is adopted as the reference framework because it reflects the standard used in both academic research and policymaking when analysing the financial environment, liquidity, and risk exposure of SMEs.

2.2 Economic significance of SMEs

Historically, in the 1960s and 1970s, large enterprises dominated the global economy, with economic policies primarily geared towards promoting mass production. In contrast, smaller enterprises were often characterised as inefficient and of limited importance in driving economic growth and prosperity (Žakelj, 2004). However, in the following decades, the progressive liberalisation of global trade, increasing competition in international markets, and the emergence of new technologies led many large enterprises to begin restructuring their operations (Žakelj, 2004). This gradual transformation reshaped the economic landscape in favour of SMEs. Today, SMEs are recognised as one of the most dynamic segments of the economy, valued for their agility, adaptability, and essential role in driving innovation, growth, and employment across different sectors (Žakelj, 2004).

In Slovenia, SMEs represent the backbone of the national economy. They account for around 99.8% of all registered enterprises, employ approximately 70% of the workforce, and generate around 65% of total business revenues, indicating their critical role in both economic output and social stability (Government of the Republic of Slovenia, n.d.). At the EU level, SMEs play a similar structural role, serving as an important driver of growth and employment. In 2024, they comprised about 26 million enterprises and provided jobs for nearly 90 million people across the EU (European Commission, 2024). Despite recent shocks, including the war in Ukraine, rising energy prices, high inflation, and supply chain disruptions, SMEs have shown strong resilience and adaptability. According to the European Commission (2024), SMEs were projected to create 824,000 new jobs in 2025, accounting for about 80% of all net employment growth, and to add €66.4 billion in real value added. Micro enterprises, in particular, were projected to outperform larger enterprises, highlighting the flexibility and innovation potential of the SME sector (European Commission, 2024). Overall, SMEs continue to form the cornerstone of the EU economy, not only in traditional labour-intensive industries such as construction, tourism, and retail, but also in fast-growing digital and creative sectors that support long-term competitiveness (European Commission, 2024).

2.3 Financial challenges of SMEs: access to finance and payment behaviour

Although SMEs are essential to economic growth and employment, their financial position is often more fragile than that of large enterprises. This section therefore focuses on two closely related challenges: access to external finance and payment behaviour. Both issues are particularly relevant for analysing liquidity and payment default risk among SMEs.

2.3.1 Access to finance

Access to financial resources depends largely on the enterprise's business performance; however, it also depends on the maturity of financial markets, government incentives, and banks' willingness to lend (Žakelj, 2004). Despite their crucial role in the economy, SMEs face

greater financial constraints than large enterprises, which may affect their productivity. Whereas large enterprises are often able to reallocate capital internally, SMEs are usually dependent on external sources of finance to fund their operations and growth (Bakhtiari et al., 2020). This dependence is further aggravated by imperfections in capital markets and information asymmetries between enterprises and lenders, which increase the cost of borrowing and may lead to credit rationing (Bakhtiari et al., 2020). Since SMEs usually do not have long credit records or sufficient collateral, their bargaining position with banks is weaker, making them more susceptible to stringent lending terms (Bakhtiari et al., 2020). Their investment decisions are also highly sensitive to internal cash flows and working capital availability, which increases their reliance on day-to-day liquidity and amplifies the risks of late payments or demand fluctuations (Bakhtiari et al., 2020). A similar link between trade credit and financing pressure is emphasised by Li et al. (2016), who argue that suppliers offering deferred payment terms may face non-payment risk and capital constraints simultaneously, as a greater use of trade credit increases financing demand. In many cases, SMEs are forced to rely on personal sources of finance, such as personal savings, family funding, or trade credit, due to limited access to formal credit; this is a further indication of their financial vulnerability. Such structural disadvantages become even more pronounced during economic recessions, when financing costs increase and banks tighten credit supply, leaving smaller enterprises more likely to face loan rejections or adverse lending terms (Bakhtiari et al., 2020).

In Slovenia, SMEs continue to face persistent difficulties in accessing external finance, although some improvement has been observed. According to the Bank of Slovenia (2025), general financing conditions in 2024 were considered better than in 2023; however, they remained below the pre-pandemic levels of 2021. Although financing conditions have improved overall, SMEs continue to face less favourable conditions than large enterprises. The share of SMEs reporting access to finance as a major constraint increased by six percentage points, indicating that the issue remains significant among smaller enterprises (Bank of Slovenia, 2025). Moreover, the European Investment Bank (hereinafter: EIB) (2024b) indicates that 74% of investment in Slovenia remains financed through internal funding, which is significantly higher than the EU average of 66%, while the share of external financing is comparatively low at 19%.

At the EU level, the latest Survey on the Access to Finance of Enterprises for the second quarter of 2025 shows that financing conditions for SMEs in the euro area remain uneven (European Central Bank, 2025). Although 14% of enterprises reported lower bank interest rates compared with the previous quarter, this improvement did not benefit all firm-size categories equally, as 2% of SMEs still faced increases. At the same time, enterprises reported that collateral requirements remained a barrier, with a net 11% of respondents perceiving them as tightened (European Central Bank, 2025). Similarly, data from the EIB Investment Survey show that most investment in the previous year was financed internally, while bank financing was the dominant source of external financing (EIB, 2024a). The biggest concern for SMEs remains the cost of financing, as 25% of them ranked it first among the aspects of external financing with which

they were most dissatisfied (EIB, 2024a). Slovenia follows the same pattern as the EU, but with an even stronger reliance on internal financing, highlighting the structural financing gap faced by its SMEs.

2.3.2 Payment behaviour and late payments

Late payments in commercial transactions have a significant impact on business operations (Ferrara & Ferraresi, 2022). Excessive delays can create liquidity problems and loss of income, thereby hindering enterprise growth and reducing job creation. Given that SMEs face stronger liquidity constraints and less favourable access to external financing, they are especially exposed to these risks (Ferrara & Ferraresi, 2022). The EU Payment Observatory Annual Report, published by the European Innovation Council and SMEs Executive Agency (hereinafter: EISMEA), further highlights a "vicious circle" between late payments and access to finance: enterprises facing late payment problems are more likely to struggle to access finance, while enterprises with severe financing constraints are also more likely to report late payment problems (EISMEA, 2025). In the long run, late payments are one of the leading causes of insolvency, accounting for one in four bankruptcies in the EU (Ferrara & Ferraresi, 2022). The report also shows that more than half of European enterprises (52%) reported facing problems due to late payments in 2024, which was five percentage points more than in 2023 and ten percentage points higher than in 2021 (EISMEA, 2025). The deterioration in payment performance is linked to the broader economic environment: 53% of enterprises reported that the economic slowdown made it harder to pay suppliers on time, while 54% stated that they were more concerned than ever about clients' ability to pay by the due date (EISMEA, 2025). This may reflect a combination of macroeconomic factors and the termination of government support measures that helped businesses overcome the COVID-19 crisis and high inflation (European Commission, 2024).

According to the most recent Intrum European Payment Report, almost half of the executives interviewed said that their revenues were not recovering as quickly as they expected, despite improvements in the broader economy (Intrum, 2025). Additionally, in this uncertain economic environment, executives' main priority is to maintain or increase liquidity, cash flows, and agility. Timely payments are critical for businesses, as they give them the flexibility needed to operate in this volatile environment. At the EU level, research shows that, on average, 11.4% of enterprises' total revenues are paid late by customers, while Slovenia records one of the highest shares, at 12.4%. This payment gap is most pronounced in the B2B sector, where the average payment gap is 17 days (Intrum, 2025).

Moreover, late payments create broader systemic risks. When one enterprise delays payment, it can trigger liquidity shortages for its trading partners, which in turn may delay their own payments, thereby amplifying financial strain across networks, particularly in long supply chains such as construction and transport (EISMEA, 2025). The report further shows that 31% of enterprises in 2024 delayed paying their own suppliers because they themselves were paid

late, illustrating a cascading effect. Beyond this ripple effect, the report identifies investment constraints as the most frequently cited consequence: 40% of respondents report negative effects on investment and growth, while 31% cite delayed payments as a threat to their survival (EISMEA, 2025). Late payments also generate a significant administrative burden, as enterprises spend on average 9.85 hours per week chasing overdue invoices. It is estimated that eliminating late payments could unlock over €100 billion per year in additional cash flow for EU micro enterprises, SMEs, and intermediate-sized enterprises (EISMEA, 2025). Finally, payment performance differs across industries: in 2024, transportation and storage recorded the lowest share of timely payments, with 65% of invoices settled on time (EISMEA, 2025).

Additional evidence from Slovenia confirms the relevance of late payment problems. The Atradius Payment Practices Barometer, an annual survey of B2B payment practices across countries, showed that 44% of total invoices in Slovenia were overdue, whereas 5% of invoices were classified as uncollectable (Atradius, 2025). Persistent late payments and liquidity constraints have contributed to a sharp rise in insolvencies. According to Coface (2025a), the number of insolvency proceedings in Slovenia increased by 32.4% in 2024 compared with the previous year. Since 2020, the number of insolvencies in Slovenia has been gradually growing, reaching 769 enterprises in 2024 (Coface, 2025a). Evidence from EU-wide surveys and national reports indicates that Slovenian SMEs face one of the highest shares of overdue invoices in the region, alongside rising insolvency rates. This demonstrates that late payments are not only a temporary disruption but also a structural risk factor that directly threatens SMEs' financial stability (Atradius, 2025; Coface, 2025a).

3 TCI – CONCEPTS AND APPLICATIONS

This chapter explains the concept, structure, and practical application of trade credit insurance. It first defines TCI and its key mechanisms, then presents the main policy types and covered risks, before discussing credit limit decisions and debt collection as important operational elements of the insurance process.

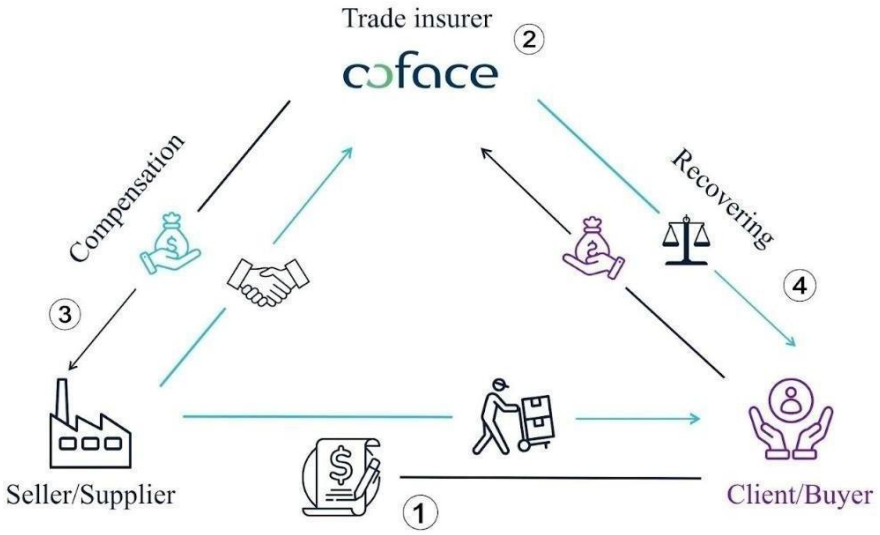
3.1 Definitions and key mechanisms of TCI

According to the International Credit Insurance & Surety Association (hereinafter: ICISA) (2015), in trade, a transaction is considered complete only when payment has been received, regardless of how transparent or well-documented the agreement may be. Enterprises often rely on open account credit arrangements, which allow buyers to generate revenues from sales and defer payment rather than settling immediately in cash. While such practices facilitate trade and business growth, the resulting trade receivables constitute unsecured capital for suppliers. Consequently, they are particularly vulnerable to commercial risks, such as insolvency or default, as well as political or systemic risks that may result in delayed or missed payments (ICISA, 2015). TCI generally distinguishes between two categories of risk: commercial and political. Commercial risk arises from the buyer's financial capacity and willingness to fulfil

payment obligations for delivered goods or services rendered. Political risk, on the other hand, is linked to the buyer's country of operation and encompasses losses resulting from events such as war, restrictive legislation, trade embargoes, or other governmental interventions that obstruct the execution of trade or prevent the insured from freely accessing the payment owed (ICISA, 2015). In today's economic environment, payment risks represent a significant business challenge, directly influencing the overall success of business operations. Effective protection against non-payment, which can negatively impact an enterprise's profitability, is therefore recognised as a key factor in ensuring sustainable business performance (Jus, 2004). TCI is a financial instrument that enables enterprises engaged in commercial transactions to protect themselves against the risk of non-payment (ICISA, 2015). As such, TCI operates in a B2B environment, and the insured parties are enterprises, not individuals (Becue, 2013).

The operational structure of TCI is built on a triangular relationship between the supplier, the buyer, and the trade credit insurer. Their interactions form a sequence that begins with the delivery of goods or services, continues with the transfer of risk to the insurer, and, in the event of default, includes indemnification and recovery. Figure 1 provides a visual overview of these core stages and the flows of obligations among the parties.

Figure 1: TCI process



Source: Own work based on Coface. (2026).

As illustrated in Figure 1, the process begins with the supplier delivering goods or services to the buyer. If the buyer fails to pay, the insurer indemnifies the supplier within the credit limit, after which the insurer undertakes recovery actions to collect the outstanding debt. Although not explicitly shown, the preventive function precedes these steps and is embedded in the insurer's ongoing credit assessments and credit limit decisions.

In the context of TCI, the insurer is the entity that provides coverage by underwriting the risk of payment default, while the insured is the party that purchases the policy and assumes the corresponding rights and obligations (ICISA, 2015). The relationship between the insurer and the insured in TCI is based on mutual interdependence. The insurer recognises that its business depends on the supplier's ability to generate sales, while suppliers acknowledge that these sales retain value only if the buyer fulfils its payment obligations (Becue, 2013). Building on this partnership, the role of the credit insurer can be understood through three core functions. The first is prevention, which involves assessing and continuously monitoring the creditworthiness and repayment capacity of buyers. On this basis, credit limits are determined as the maximum balance that may be outstanding at any given time. These limits are intended to reconcile the supplier's commercial objectives with the insurer's tolerance for risk, although overly restrictive limits may reduce the supplier's negotiating power with buyers. The second function is indemnification, whereby the insurer provides compensation when a buyer covered by an agreed credit limit fails to meet its payment obligations (Becue, 2013). In return, the insured pays a premium, typically calculated as a percentage of insured turnover, outstanding receivables, or the credit limits granted, depending on the policy structure. The premium rate should reflect the average credit risk of the portfolio of buyers (ICISA, 2015). The third function is recovery, which extends beyond indemnification by engaging the insurer and the insured in joint efforts to reclaim outstanding debts. Such efforts may involve initiating legal proceedings against the defaulting buyer or arranging structured repayment schemes designed to secure full or partial settlement of the obligation (Becue, 2013).

3.1.1 Policy types

TCI policies impose a maximum liability, which sets the upper limit on the insurer's total compensation for losses arising from commercial or political risks during a single policy year (ICISA, 2015). This limit is generally defined as either a predetermined fixed amount or as a multiple of the annual premium. TCI policies typically cover both domestic and export sales, providing indemnification for approximately 80–90% of insured receivables (ICISA, 2015). The policy's purpose is not only to indemnify losses but also to help suppliers avoid them, thereby supporting business growth. Claims are paid only when a valid, legally enforceable debt exists, and disputes over goods or services are excluded. In cases of insolvency, written acknowledgement of the debt by the receiver is required (Jones, 2010).

Policies can be classified according to the level of risk selection allowed under the TCI arrangement (ICISA, 2015). The broadest and most traditional form is the whole turnover policy, which insures all B2B transactions of the enterprise and provides the widest risk diversification. More restrictive options include coverage for a selected part of turnover, such as domestic sales, export sales, or a specific product line, as well as coverage for selected buyers, typically based on objective criteria such as outstanding amounts or exposure size. The narrowest form is single-buyer or single-contract cover, which applies to a transaction with one

buyer or even a single deal. In general, the wider the spread of the risk, the more likely insurers are to accept the risk and offer more favourable premium terms (ICISA, 2015).

TCI policies may also be classified by the type of customer they are designed for (ICISA, 2015). In addition to standard policies for the mid-market, insurers may offer simplified, entry-level solutions for micro-SMEs, and highly tailored, multi-currency and multi-jurisdictional programmes for multinationals. Products can also be sector-specific, with features adapted to the particular risks of industries such as construction or recruitment. For large enterprises with strong internal credit management, insurers provide excess-of-loss policies, which only indemnify losses above a significant self-retained amount. These contracts grant greater autonomy in setting credit limits but require strict adherence to documented credit management procedures, as any breach may invalidate coverage (ICISA, 2015).

3.1.2 Risk types and causes of loss

TCI protects enterprises against losses arising from a buyer's failure to pay for goods or services supplied on credit terms. The types of risk causing non-payment losses most commonly covered by trade credit insurers are insolvency, protracted default, and political risks (ICISA, 2015).

a) Commercial risk

Commercial risk arises from a deterioration in the financial situation of a private buyer (Jus, 2004). It may result from various financial or behavioural factors on the debtor's side. In the context of commercial risks, non-payment typically occurs either because of the buyer's permanent insolvency, such as bankruptcy, compulsory settlement, or similar proceedings, or because of protracted default, meaning a prolonged delay in payment, usually around six months after the due date. In some cases, losses may also occur due to the buyer's unilateral termination or repudiation of the contract, or refusal to take delivery of the supplied goods (Jus, 2004). Debtor default may result from a wide range of interrelated factors. Frequent causes of buyer insolvency include ineffective management practices, high operating costs, excessive expansion, inadequate financial oversight, and failure to adapt promptly to changing market conditions, among others (Jus, 2004).

Insolvency refers to a judicial or administrative process in which a buyer's assets and financial affairs come under court or legally appointed supervision for the purpose of restructuring, liquidating, or otherwise settling outstanding debts. Although the specific procedures differ across jurisdictions, insolvency generally represents the formally recognised inability of a debtor to meet its financial obligations (ICISA, 2015). Insolvency coverage under TCI generally extends to situations where the buyer's financial failure has been legally recognised, and in some cases, to events deemed comparable to insolvency, such as extrajudicial settlements with creditors or unenforced court judgments. Once insolvency occurs, the insured's loss is considered definite, even though the final amount of loss depends on the recovery prospects from the insolvent estate. Under most policies, outstanding receivables owed by the insolvent

buyer, whether already due or not at the date of insolvency, are indemnified, subject to the specific terms and conditions of the insurance contract (ICISA, 2015).

Protracted default refers to a situation in which the buyer fails to settle the contractual debt within a period specified in the TCI policy, commonly referred to as the waiting period. This period is usually calculated either from the original due date of the receivable or from the date when the insured submits a claim or transfers the collection of the unpaid debt to the insurer. In practice, the waiting period typically ranges from four to six months. Unlike insolvency, where the loss is formally established through insolvency proceedings, under protracted default coverage, a claim becomes payable once this predefined period has expired (ICISA, 2015).

b) Political risk

Political risk coverage in TCI protects exporters and suppliers from losses caused by events in the buyer's country that are beyond the control or responsibility of the individual buyer (ICISA, 2015). Such country risks may include government-imposed payment restrictions, currency inconvertibility, confiscation of goods, embargoes, or acts of political violence such as war, civil unrest, or terrorism (ICISA, 2015; Coface, 2024). Depending on the insurer's policy wording, coverage may also extend to events occurring outside the seller's or buyer's country, referred to as third-country risks (ICISA, 2015). As highlighted by Coface (2024), the nature of political risk has evolved beyond traditional threats such as war or expropriation to encompass economic sanctions, trade embargoes, climate-related disruptions, and broader geopolitical instability, all of which can obstruct international transactions and payment flows. In this context, political risk insurance plays a crucial role in safeguarding enterprises against non-payment and ensuring business continuity in an increasingly uncertain global environment **(**Coface, 2024**)**. While political risk forms part of the broader TCI framework, the empirical analysis in this thesis focuses on commercial payment risk and its firm-level financial implications for SMEs. Commercial payment risk is reflected primarily in receivables collection efficiency and blocked-account incidence, while liquidity indicators capture the related short-term financial position of firms.

3.1.3 Credit limit decisions

Buyer risk underwriting in TCI is operationalised through buyer-specific credit limits, which define the maximum exposure the insurer is willing to cover for each buyer and therefore link risk assessment directly to coverage. In practice, the limit decision starts with the insured's request for a buyer-specific credit limit that reflects the intended trading exposure under agreed payment terms (ICISA, 2015). A simple and commonly used approximation for the requested exposure in regular trading is shown in equation (1):

$$Requested\ limit\ =\ A\ \times\ (B\ +\ 1)\ (1)$$

Equation (1) captures the fact that longer payment terms mechanically increase the peak number of receivables outstanding. In this expression, A represents average monthly turnover, calculated as annual turnover divided by 12, while B represents the actual payment period expressed in months. The additional month in the formula reflects the possibility that new deliveries may continue while receivables from the previous period remain outstanding, thereby increasing the peak exposure. The requested amount is therefore an exposure-driven figure from the supplier's perspective rather than a guarantee that the full amount is insurable (Becue, 2013).

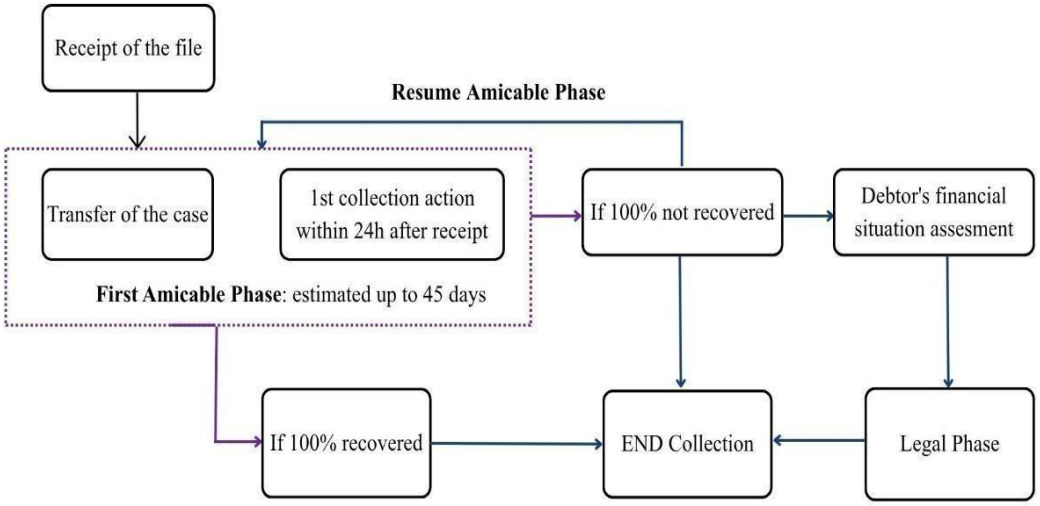
After receiving the relevant buyer information, the insurer determines an approved credit limit and may grant full acceptance, partial acceptance, or refusal of the requested amount (ICISA, 2015). Full acceptance reflects strong underwriting confidence in the buyer's ability to pay and in the appropriateness of the requested exposure. Partial acceptance indicates that the insurer has limited confidence and either retains doubts about timely repayment or judges that the requested limit is not consistent with the buyer's financial situation. A refusal likewise signals a lack of trust in the buyer's creditworthiness, commonly associated with adverse indicators such as weak business performance or the accumulation of unpaid invoices (Becue, 2013). Beyond simply reducing or refusing limits, the insurer may impose conditions, such as revised maximum payment periods or information requirements, that operate as underwriting controls intended to limit potential losses. Accordingly, a limit shortfall, where the approved limit is lower than the requested limit, can be treated as an underwriting signal that the buyer belongs to a higher-risk segment, even if trade continues under a reduced insured exposure (Becue, 2013). Under this logic, buyers with systematically reduced limits should exhibit a higher propensity for payment default outcomes and, consequently, a higher likelihood that transactions with those buyers will generate claims (ICISA, 2015). Although credit-limit decisions are not directly tested in the empirical analysis, they are relevant for understanding the preventive mechanism through which TCI may influence receivables management and payment-risk exposure.

3.1.4 Debt collection

One of the key components of a TCI policy is the debt collection process, which becomes relevant when receivables remain unpaid after their due date (ICISA, 2015). The policyholder is expected to maintain sound credit management practices and closely monitor outstanding receivables. Once the insured becomes aware that a payment default is likely or has already occurred, the insured is expected to take all reasonable and timely measures to mitigate potential losses. This includes enforcing securities, exercising retention of title rights, and, if necessary, initiating legal proceedings. Such actions must be taken in accordance with the insurer's instructions and with prior consent before entering into settlements, repayment plans, or similar agreements. Importantly, credit insurers expect policyholders to manage and monitor buyers as if no insurance coverage were in force.

When an invoice remains overdue, the insured should promptly initiate collection efforts by sending reminders, contacting the buyer, and identifying any potential disputes at an early stage. Most TCI policies also allow continued deliveries to buyers with overdue payments within a predefined maximum extension period, typically ranging from 30 to 90 days after the invoice due date. The duration of this period may depend on factors such as the buyer's country, sector, or financial condition, and continued deliveries are only permissible if the approved credit limit remains sufficient (ICISA, 2015). Figure 2 provides an overview of the debt collection workflow under a TCI policy, showing the progression from the initial amicable collection steps to the legal phase if the outstanding debt is not fully recovered.

Figure 2: Debt collection process under TCI



Source: Own work based on Coface. (2026).

The debt collection process presented in Figure 2 shows that collection under TCI follows a structured sequence, from monitoring and reminders to amicable collection and, if necessary, legal recovery. This process is particularly relevant for SMEs because it supports more systematic follow-up of overdue receivables and helps reduce the risk that payment delays develop into more serious financial distress (ICISA, 2015; Becue, 2013).

3.2 Strategic and operational benefits of TCI for SMEs

The primary advantage of TCI lies in its role as a risk management tool that protects an enterprise's trade receivables and safeguards cash flow in the event of buyer non-payment (ICISA, 2015). Beyond financial protection, TCI also serves a strategic function, enabling enterprises, particularly SMEs, to strengthen their competitive position by offering more attractive credit terms, expanding into new markets, and extending higher credit limits with reduced risk exposure (ICISA, 2015). By mitigating uncertainty in trade transactions, TCI

allows enterprises to pursue business opportunities that might otherwise be deemed too risky, thereby supporting market diversification and export growth (Jus, 2004).

From an operational perspective, TCI enhances internal credit management practices by encouraging systematic monitoring of buyers' financial status and providing access to reliable credit information, which leads to more informed and timely commercial decisions (ICISA, 2015). The insurance framework also reduces administrative burdens, as specialised insurers often provide complementary services such as credit risk assessment, monitoring, and debt collection—functions that would otherwise require significant in-house resources. This outsourcing allows SMEs to focus on their core business activities while simultaneously benefiting from professional credit management expertise (Jus, 2004). This practical role is also supported by Lezgovko and Jakovlev (2017), who evaluate TCI as a credit risk management tool and find that its value lies in debtor assessment, debt collection, risk monitoring, cash-flow control, and the reduction of overdue-account frequency and the volume of overdue invoices. TCI also contributes to improved liquidity and financing capacity. By minimising bad-debt provisions and shortening collection periods, insured enterprises may achieve stronger cash flow and enhanced credibility with financial institutions, facilitating access to bank loans and other financing instruments under more favourable terms (ICISA, 2015). Furthermore, by transferring payment risks to specialised insurers, enterprises can strengthen their financial stability and creditworthiness, aligning risk management with broader business strategy (Jus, 2004). Insured receivables can be perceived as less risky by lenders and factoring providers, improving access to short-term financing and supporting liquidity management (Jones, 2010).

For SMEs, the operational value of TCI is particularly important because many smaller enterprises do not have specialised credit-management departments or advanced internal systems for assessing buyer risk. In such cases, the insurer's credit information, monitoring, and collection infrastructure can partly compensate for limited internal resources. This means that TCI may influence financial outcomes not only through indemnification after default, but also through earlier identification of risky buyers, more disciplined credit-limit decisions, and more systematic follow-up of overdue receivables. These functions are especially relevant for indicators such as DSO and blocked-account incidence, which reflect the efficiency of receivables collection and exposure to more severe payment-related distress (ICISA, 2015; Becue, 2013).

At a broader macroeconomic level, TCI generates benefits that indirectly reinforce SME performance. By supporting safer trade participation, both domestically and internationally, TCI promotes economic stability, export competitiveness, and improved payment discipline within markets. Through the dispersion of risk, partly via international reinsurance, it also helps prevent systemic financial disruptions such as cascading bankruptcies (Jus, 2004).

4 ABOUT COFACE

This chapter presents Coface as the institutional context for the empirical part of the thesis. It first provides an overview of the Coface Group and its global presence, then explains its role in the Slovenian credit insurance market, and finally outlines the main products and services offered by Coface Slovenia.

4.1 Overview of Coface Group and its global presence

Coface is a multinational trade credit insurance company headquartered in Bois-Colombes, France, specialising in the assessment, management, and insurance of commercial credit risks. Established in 1946, Coface has become one of the leading players in the global credit insurance market, providing solutions that help enterprises protect against non-payment by domestic and international buyers (Coface, n.d.a). Originally founded as a public entity to support French exports, the company was privatised in 1994 and has been listed on Euronext Paris since 2014. It is partly owned by Arch Capital Group Ltd., a Bermuda-based global reinsurance organisation, which is the largest shareholder with 29.5% of the company's capital, while the remaining shares are publicly held (Coface, n.d.a).

The Group's core activities include credit insurance, business information, debt collection, and risk assessment services, which together support enterprises in monitoring buyer risk and stabilising cash flow (Coface, n.d.b). Coface operates directly or through partner networks in nearly 100 countries, serving around 100,000 clients and covering approximately 200 markets worldwide. The company employs more than 5,200 professionals and has regional headquarters in Paris, Mainz, Warsaw, Singapore, and New York (Coface, n.d.c). Together with Allianz Trade, formerly Euler Hermes, and Atradius, Coface belongs to the group of major global trade credit insurers that collectively account for most of the world's insured trade credit exposure (AU Group, 2024). By combining global risk monitoring with local market insight, Coface provides tools that are particularly relevant for SMEs using TCI to manage payment default risk (Coface, n.d.b).

4.2 Role of Coface in the Slovenian credit insurance market

Coface's presence in the Slovenian credit insurance market represents a significant development in the evolution of the country's trade credit infrastructure and risk management practices. Coface entered the Slovenian credit insurance market through the acquisition of SID-PKZ, the credit insurance subsidiary of SID Bank, in 2019. The transaction, announced in 2018 and completed in April 2019, marked a major step in Coface's expansion in Central and Eastern Europe (hereinafter: CEE) (Coface, 2019). Before the acquisition, SID-PKZ had held a leading position in the Slovenian market, with an annual turnover of approximately €14 million and an insured exposure exceeding €90 million, serving both exporting enterprises and SMEs (Coface, 2019). By incorporating PKZ, Coface strengthened its regional presence and expanded its

ability to provide integrated credit insurance, business information, and debt collection services across CEE.

Following the acquisition, Coface Slovenia became part of the CEE regional cluster, headquartered in Warsaw. Through this structure, the Slovenian subsidiary gained access to global underwriting tools, economic research, and risk monitoring systems that strengthen the overall resilience of the national credit insurance market (Coface, 2019). Coface's presence has also contributed to stronger competition and professionalisation within the Slovenian market, encouraging local enterprises to adopt more systematic approaches to managing receivables and payment risk. In an economy as open and export-oriented as Slovenia's, where exports account for over 80% of gross domestic product, TCI is an important instrument for safeguarding liquidity and supporting growth (Eurostat, 2025). Coface's products and services directly support this function by providing enterprises, particularly SMEs, with protection against buyer insolvency and delayed payments, enabling them to extend credit more confidently to domestic and foreign partners (Coface, n.d.d). Through these activities, Coface has become a key player in the Slovenian credit insurance landscape, bridging local business needs with international best practices in credit risk management (Coface, 2019).

4.3 Coface Slovenia – product portfolio

Coface structures its TCI products in Slovenia according to the size, turnover, and international exposure of the insured enterprises (Coface, n.d.e). EasyLiner is designed for SMEs with an annual insurable turnover of approximately €50,000 to €10 million. It provides protection against unpaid invoices arising from domestic or export transactions and is based on a simplified whole-turnover policy. Coverage is provided on a risk-attaching basis, typically renewed automatically on an annual basis, and focuses on commercial risks linked to buyer insolvency or protracted default (Coface, n.d.f). Its streamlined structure is intended for enterprises seeking straightforward risk coverage without extensive administrative requirements.

The second tier, TradeLiner, is designed for larger enterprises with turnover exceeding €10 million and more complex buyer portfolios. It offers a flexible policy structure that covers either the entire receivables portfolio or specific buyers and can be extended to political and natural-disaster risks. This product is suitable for enterprises requiring more customised protection aligned with diverse customer bases or international operations (Coface, n.d.g). The GlobaLiner solution is tailored for large multinational enterprises that manage credit risks across multiple countries and require a unified framework for policy administration (Coface, 2021). It provides a master policy structure that centralises risk management at the corporate level while maintaining local insurance contracts in each participating country to ensure compliance with national legal and tax requirements. By integrating global oversight with localised implementation, GlobaLiner enhances transparency and coordination between headquarters and

regional entities, reducing administrative complexity and potential protection gaps (Coface, 2021).

In addition to insurance coverage, Coface provides information services and debt collection services that function as analytical extensions of its underwriting activities, supporting enterprises in assessing and managing credit risk more systematically (Coface, n.d.b). Through a global database encompassing information on more than 200 million enterprises, Coface provides access to buyer credit ratings, country-risk indicators, and sectoral analyses, allowing Slovenian enterprises to base their credit decisions on verified data and to adopt a more preventive approach to receivables management (Coface, 2025b). Taken together, Coface's insurance, information, and collection services represent an integrated framework for trade credit risk management, which may contribute to greater payment discipline, improved liquidity, and reduced default exposure among Slovenian enterprises, particularly SMEs engaged in export activities.

5 RESEARCH AND HYPOTHESIS TESTING

This chapter presents the empirical framework used to examine the relationship between TCI, liquidity, and payment default risk among Slovenian SMEs. It first explains the research design, then defines the key constructs and measurement approach, and finally develops the hypotheses tested in the empirical analysis.

5.1 Research design

This master's thesis employs a quantitative case study approach, focusing on Coface Slovenia. The aim is to assess how TCI is associated with liquidity and payment default risk among Slovenian SMEs, using internal Coface data. The empirical analysis covers the period from 2022 to 2024, allowing the observation of firm-level financial indicators alongside payment behaviour and default-related outcomes over multiple years within a consistent institutional and operational setting. The research design follows a comparative firm-level framework based on a single dataset used to test both hypotheses. The analysis compares SMEs insured under Coface's TCI policies with a benchmark group of non-insured SMEs that used Coface collection services during the same period. This benchmark group provides a relevant comparison group within the Coface environment, as these firms had a documented commercial relationship with Coface but did not have active TCI coverage. The analysis examines two related dimensions: the first focuses on liquidity, captured through standard accounting-based indicators, whereas the second focuses on commercial payment default risk, assessed through DSO and blocked-account incidence. Together, these dimensions allow the thesis to compare insured and non-insured SMEs in terms of liquidity, receivables collection efficiency, and payment-related financial distress.

5.2 Key constructs and measurement approach

In this thesis, TCI refers to insurance coverage that protects the insured supplier against losses arising from buyer insolvency or protracted default. Liquidity is understood as an SME's short-term ability to meet current obligations and to absorb payment shocks. In the empirical analysis, liquidity is captured through standard firm-level indicators derived from financial statements, namely the cash ratio, current ratio, quick ratio, and NWC/TA.

Payment default risk is understood as the risk of adverse payment outcomes and payment-related financial distress arising from delayed receivables collection and difficulties in meeting short-term financial obligations. In this thesis, payment default risk is assessed at the SME level using DSO and blocked-account incidence. DSO reflects the average time needed to collect receivables and therefore captures receivables collection efficiency, while blocked-account incidence captures whether a firm experienced a more severe form of payment-related financial distress. Together, these variables provide practical firm-level proxies for payment default risk.

5.3 Hypothesis development

Building on the theoretical background and the measurement approach outlined above, this section develops two hypotheses. The first concerns the potential association between TCI and liquidity, while the second examines the expected relationship between TCI and payment default risk.

5.3.1 Liquidity effects of TCI

SMEs generally have more limited financial buffers than large enterprises and depend strongly on the timely collection of receivables to finance daily operations (Bakhtiari et al., 2020). TCI can influence SME liquidity primarily through its risk-transfer function, as indemnification may mitigate the financial impact of severe buyer non-payment and reduce unexpected cash flow shocks when policy conditions are met (ICISA, 2015). In addition, although more indirect, the presence of TCI may encourage more cautious receivables management by strengthening risk awareness and prompting closer internal monitoring of outstanding trade receivables (Becue, 2013). Therefore, SMEs covered by TCI are expected to exhibit stronger short-term financial capacity than comparable non-insured SMEs. This expectation is formalised in the following hypothesis.

H1: SMEs covered by TCI exhibit stronger liquidity than non-insured SMEs.

In the empirical analysis, liquidity is proxied using multiple firm-level indicators, including the cash ratio, current ratio, quick ratio, and NWC/TA. These measures capture complementary aspects of short-term financial capacity. The exact construction of each indicator and the testing approach are presented in the following sections.

5.3.2 TCI and payment default risk

In addition to supporting liquidity, TCI may also be associated with lower payment default risk at the firm level. SMEs are often highly exposed to delayed receivables collection, irregular buyer payment behaviour, and cash flow disruptions caused by non-payment (Ferrara & Ferraresi, 2022). By transferring part of the receivables risk to the insurer and embedding receivables monitoring into business practice, TCI may contribute to more disciplined receivables management and lower exposure to payment-related distress (Becue, 2013). This expectation is consistent with studies linking credit insurance to payment-risk mitigation: Li et al. (2016) show theoretically that TCI can reduce the supplier's default risk, while Ji et al. (2026) identify payment-risk mitigation as one of the main channels through which export credit insurance affects firm outcomes.

In this thesis, payment default risk is examined at the SME level using indicators that reflect both the efficiency of receivables collection and the presence of serious payment-related financial distress. The first indicator is DSO, which captures the average time required to collect receivables. A higher DSO indicates slower collection and, therefore, greater exposure to payment delays. The second indicator is account blockage, which represents a more severe manifestation of payment and liquidity problems. A blocked account may indicate that the enterprise is experiencing substantial payment-related financial difficulties and therefore represents a more severe form of payment default risk than delayed receivables collection alone.

Accordingly, SMEs covered by TCI are expected to display lower payment default risk than comparable non-insured SMEs. This expectation is formalised in the following hypothesis.

H2: SMEs covered by TCI exhibit lower payment default risk than non-insured SMEs, as reflected in more efficient receivables collection and a lower incidence of account blockage.

6 METHODOLOGY

This chapter presents the empirical framework used to examine the relationship between TCI, liquidity, and payment default risk among Slovenian SMEs. It first explains the research design, then defines the key constructs and measurement approach, and finally develops the hypotheses tested in the empirical analysis.

6.1 Dataset and sample construction

For the empirical analysis, a firm-level dataset was constructed using anonymised internal Coface Slovenia data for the period 2022–2024. The unit of observation is a single SME, defined in line with the EU definition adopted in this thesis. Financial indicators were calculated as average values over the three-year period, so that each firm appears only once in the final

dataset. The sample consists of two groups: SMEs insured under Coface TCI policies and a benchmark group of non-insured enterprises that used Coface debt collection services during the same period.

The dataset is restricted to firms for which the necessary balance sheet and income statement items are available to calculate the selected liquidity indicators. Since the analysis focuses exclusively on Slovenian enterprises, the underlying financial statement data originate from the Agency of the Republic of Slovenia for Public Legal Records and Related Services (AJPES) and were obtained via Coface Slovenia's internal data extract. To ensure consistency and comparability, observations with missing key inputs were excluded, and duplicate observations were removed where identified. In addition, outliers in the liquidity indicators were treated by winsorising the relevant variables at the 1st and 99th percentiles to reduce the influence of extreme values while preserving all observations in the sample.

The initial dataset consisted of 428 enterprises. A total of 33 enterprises were excluded from the final sample for the following reasons: nine enterprises were established after 2022 and therefore did not have financial data available for the full three-year period; seven enterprises were deleted from the business register during the observation period; eight enterprises did not have financial data available for all three years because their annual reports were not published; and nine duplicate observations were removed. These duplicates related to enterprises that held a valid TCI policy but also appeared in the debt collection records. To preserve a unique firm-level observation structure, such enterprises were retained only once and classified as insured SMEs.

After these exclusions, the final dataset consists of 395 enterprises, of which 238 are insured and 157 are non-insured. Each enterprise represents one observation in the empirical analysis. The non-insured group serves as the benchmark group and includes enterprises that used Coface debt collection services between 2022 and 2024 but did not hold a valid TCI policy during that period. The final analytical sample includes only firms classified as micro, small, or medium-sized enterprises, ensuring full consistency with the EU SME definition adopted in this thesis. Requiring data availability for the full 2022–2024 period improves comparability across firms, although it may also reduce sample representativeness by excluding newly established or discontinued enterprises.

6.2 Variable definitions

The empirical analysis is conducted at the firm level, with each SME representing one observation. The main explanatory variable is insurance status, distinguishing insured SMEs from non-insured SMEs. The dependent variables are grouped into two dimensions: liquidity, measured by the cash ratio, current ratio, quick ratio, and NWC/TA; and payment default risk, measured by DSO and blocked-account incidence. DSO is treated as a continuous variable, while blocked-account incidence is treated as a binary variable. Table 1 summarises the

operational definitions and measurements of all variables used in the empirical analysis, including the control variables for firm size and industry sector.

Table 1: Variable definitions

Variable	Role in analysis	Type of variable	Operational definition	Measurement
Insurance status	Main explanatory variable	Categorical (nominal, dummy variable)	Indicates whether the SME had active TCI coverage.	1 = insured, 0 = non-insured
Cash ratio	Dependent variable (liquidity – H1)	Numerical (continuous, ratio)	Measures the firm's ability to meet short-term obligations using only the most liquid assets.	Cash and cash equivalents / Current liabilities
Current ratio	Dependent variable (liquidity – H1)	Numerical (continuous, ratio)	Measures the ability of a firm to cover current liabilities with current assets.	Current assets / Current liabilities
Quick ratio	Dependent variable (liquidity – H1)	Numerical (continuous, ratio)	Measures short-term liquidity excluding inventories.	(Current assets – Inventories) / Current liabilities
NWC/TA	Dependent variable (liquidity – H1)	Numerical (continuous, ratio)	Measures net working capital relative to total assets.	(Current assets – Current liabilities) / Total assets
DSO	Dependent variable (payment default risk – H2)	Numerical (continuous, ratio)	Measures the average number of days required to collect receivables.	(Accounts receivable / Net sales) × 365
Blocked-account incidence	Dependent variable (payment default risk – H2)	Categorical (nominal, dummy variable)	Indicates whether the firm had a blocked account during the observed period.	1 = yes, 0 = no
Firm size	Control variable	Categorical (ordinal)	Controls for differences in firm size among SMEs.	Micro / Small / Medium
Industry sector	Control variable	Categorical (nominal)	Controls for differences in industry affiliation.	Capital goods / transport-related manufacturing; Process / consumer manufacturing and agro; Commercial and services; Construction

Source: Own work based on Coface Slovenia data. (2026).

Since annual firm-level values may be affected by temporary fluctuations, the main analysis uses firm-level average values over the 2022–2024 period. The selected dependent variables were chosen because they capture complementary aspects of liquidity and payment default risk. The liquidity indicators range from narrow cash-based measures to broader measures of short-term solvency and working capital position. For payment default risk, DSO captures receivables collection efficiency and exposure to payment delays, while blocked-account incidence indicates whether the firm experienced a more severe form of payment-related financial distress.

In addition to the main explanatory variable and the dependent variables, the dataset contains firm characteristics used for descriptive and control purposes, namely firm size and industry sector. Both variables are treated as categorical control variables in the regression analysis, as they are included to account for structural differences between firms that may influence liquidity and payment behaviour. Firm size is based on the SME size classification available in the dataset, distinguishing between micro, small, and medium-sized enterprises, in line with the EU SME classification adopted in this thesis. Industry sector is captured through the aggregated NACE sector classification, which groups firms into four broader industry categories: Construction; Commercial and services; Process / consumer manufacturing and agro; and Capital goods / transport-related manufacturing. This aggregation was used to provide a more concise sectoral classification and to avoid excessive fragmentation across individual industry categories.

6.3 Empirical strategy

The empirical analysis is conducted at the firm level and is structured in three steps. The purpose of this approach is to first provide a descriptive overview of the sample, then test whether differences between insured and non-insured SMEs are statistically significant, and finally examine whether the observed relationships remain after controlling for firm size and industry sector.

The first step of the empirical analysis consists of descriptive statistics. The numerical dependent variables are summarised first for the total sample and then separately for insured and non-insured SMEs. For each variable, the table reports the mean, median, standard deviation, minimum, and maximum. This structure provides an initial comparison of liquidity and payment default risk indicators between the two groups before formal statistical testing is applied.

The second step of the empirical analysis consists of hypothesis testing. After the descriptive comparison of insured and non-insured SMEs, formal statistical tests are applied to examine whether the observed differences between the two groups are statistically significant. Welch's two-sample t-tests are applied to numerical indicators to assess whether the mean values of insured and non-insured SMEs differ significantly. These tests are used for the liquidity indicators and DSO. For blocked-account incidence, a chi-square test of independence is

applied to examine whether the occurrence of account blockage is associated with insurance status. These tests provide an initial statistical assessment of the two hypotheses before the regression analysis is conducted.

The third step consists of regression analysis. The purpose of this step is to examine whether insurance status remains associated with the selected liquidity and payment default risk indicators after controlling for firm size and industry sector. Insurance status is used as the key explanatory variable, while firm size category and industry sector classification are included as categorical control variables. The regression analysis is organised according to the type of dependent variable and the corresponding estimation method. For continuous dependent variables, ordinary least squares (hereinafter: OLS) regression models are estimated. These models are applied to the four liquidity indicators related to H1 and to DSO, which is the continuous payment default risk indicator related to H2. The general regression specification used for these models is presented in equation (2):

$$Y_i = \alpha + \beta\, Insurance_i + \gamma\, Size_i + \delta\, Sector_i + \varepsilon_i \quad (2)$$

In equation (2), Y_i denotes the relevant firm-level outcome variable. $Insurance_i$ is the key explanatory variable and indicates whether the enterprise is insured under a Coface TCI policy. $Size_i$ represents the firm size category, while $Sector_i$ represents the industry sector classification. The error term is denoted by ε_i. The coefficient of main interest is β, which captures the association between insurance status and the dependent variable, after controlling for firm size and industry sector.

Since blocked-account incidence is a binary dependent variable, it is analysed using logistic regression. This model estimates whether SMEs covered by TCI have a different likelihood of experiencing account blockage compared with non-insured SMEs, after controlling for firm size and industry sector. The results are reported through coefficients, p-values, odds ratios, and 95% confidence intervals. This logistic regression model provides the second regression-based test of H2, complementing the OLS model for DSO.

By combining descriptive statistics, hypothesis testing, and regression analysis, the empirical strategy enables a gradual assessment of the relationship between TCI and SME financial outcomes. The descriptive statistics provide an initial comparison of insured and non-insured SMEs, the hypothesis tests assess the statistical significance of group differences, and the regression models examine whether insurance status remains associated with liquidity and payment default risk after accounting for selected firm-level controls. Since the dataset is observational, the results are interpreted as evidence of association rather than causal effects.

7 RESULTS

This chapter presents the empirical results of the analysis. It first describes the sample and the main variables, then reports the hypothesis tests, followed by the regression models used to

assess whether insurance status remains associated with liquidity and payment default risk after controlling for firm size and industry sector. The chapter concludes with a summary of the main findings in relation to H1 and H2.

7.1 Descriptive statistics

The categorical variables include insurance status, blocked-account incidence, firm size, and industry sector. These variables describe the composition of the sample, while firm size and industry sector are later included as control variables in the regression models.

The final analytical sample consists of 395 SMEs, of which 238 are insured and 157 are non-insured. Insured SMEs therefore account for 60.3% of the sample, while non-insured SMEs represent 39.7%. Blocked-account incidence is observed in 50 enterprises, or 12.7% of the total sample, while 345 enterprises did not experience account blockage. This indicates that account blockage is not widespread across the sample but is concentrated among a smaller subset of firms. The sample is relatively balanced across firm size categories. Small enterprises represent the largest group, while micro and medium-sized enterprises each account for a similar share of the sample. In terms of industry sector, the largest group is capital goods and transport-related manufacturing, followed by process and consumer manufacturing and agro, commercial and services, and construction. These patterns support the inclusion of firm size and industry sector as control variables in the subsequent regression models since liquidity conditions and payment behaviour may differ across firms depending on their size and sector. Table 2 summarises the distribution of categorical variables used in the empirical analysis.

Table 2: Distribution of categorical variables used in the empirical analysis

Variable	Categories	Number of observations	Share of total sample (%)
Insurance status	Insured	238	60.3
	Non-insured	157	39.7
Blocked-account incidence	Yes	50	12.7
	No	345	87.3
Firm size	Micro	122	30.9
	Small	151	38.2
	Medium	122	30.9
Industry sector	Capital goods / transport-related manufacturing	141	35.7
	Process / consumer manufacturing and agro	113	28.6
	Commercial and services	75	19.0
	Construction	66	16.7

Source: Own work based on Coface Slovenia data. (2026).

After presenting the sample structure, the analysis turns to the numerical dependent variables used to assess liquidity and payment default risk. Table 3 reports the descriptive statistics for the numerical dependent variables, first for the total sample and then separately for insured and non-insured SMEs**.** For each variable, the table presents the mean, median, standard deviation, minimum, and maximum values. This allows a preliminary comparison of the two groups before formal hypothesis testing and subsequent regression models are conducted.

Table 3: Descriptive statistics of numerical dependent variables by insurance status

Dependent variable	Group	Mean	Median	Standard deviation	Minimum	Maximum
Cash ratio	Total sample (N = 395)	0.491	0.192	0.795	0.000	4.818
	Insured (N = 238)	0.510	0.198	0.812	0.000	4.810
	Non-insured (N = 157)	0.463	0.179	0.769	0.000	4.818
Current ratio	Total sample (N = 395)	2.468	1.791	2.075	0.217	14.780
	Insured (N = 238)	2.643	1.973	2.109	0.217	14.780
	Non-insured (N = 157)	2.202	1.560	1.999	0.217	11.292
Quick ratio	Total sample (N = 395)	1.750	1.260	1.633	0.105	11.070
	Insured (N = 238)	1.796	1.313	1.651	0.113	11.070
	Non-insured (N = 157)	1.679	1.185	1.609	0.105	9.295
NWC/TA	Total sample (N = 395)	0.243	0.240	0.265	-0.777	0.882
	Insured (N = 238)	0.290	0.282	0.233	-0.478	0.882
	Non-insured (N = 157)	0.173	0.180	0.294	-0.777	0.833
DSO	Total sample (N = 395)	74.219	62.735	64.051	5.091	578.932
	Insured (N = 238)	67.106	57.748	52.644	6.332	529.700
	Non-insured (N = 157)	85.002	69.112	77.181	5.091	578.932

Source: Own work based on Coface Slovenia data. (2026).

At the total sample level, the liquidity indicators suggest a generally positive short-term financial position, although there is considerable variation across firms. This variation is visible in the difference between mean and median values, particularly for the cash ratio, where the mean is 0.491 and the median is 0.192, indicating that cash holdings are unevenly distributed across SMEs. The mean current ratio of 2.468 and the mean NWC/TA ratio of 0.243 further suggest that, on average, firms in the sample hold current assets above current liabilities and maintain a positive net working capital position relative to total assets.

The group-level results suggest that insured SMEs generally exhibit more favourable liquidity indicators than non-insured SMEs. Across all four liquidity measures, both mean and median values are higher for insured firms. However, the differences are relatively modest for the cash ratio and quick ratio, while they are more pronounced for the current ratio and NWC/TA. This pattern suggests that differences between insured and non-insured SMEs are more evident in broader measures of short-term solvency and working capital position than in narrower liquidity indicators.

For payment default risk, the descriptive results also suggest differences between the two groups. At the total sample level, the mean DSO is 74.219 days, while the median is 62.735 days, suggesting that receivables collection periods vary across firms. Non-insured SMEs have a higher mean and median DSO than insured SMEs, indicating slower receivables collection and greater exposure to payment delays among non-insured firms. The relatively high standard deviation values and wide minimum–maximum range for DSO indicate substantial variation in payment behaviour across the sample. This suggests that payment-related outcomes are unevenly distributed, with more severe payment delays concentrated among a smaller number of enterprises.

These descriptive findings provide an initial indication that insured and non-insured SMEs differ across both dimensions of the analysis. The differences appear more pronounced for broader liquidity measures and DSO than for narrower liquidity measures such as the cash ratio. However, descriptive statistics alone do not show whether the observed differences are statistically significant. The next section therefore applies formal hypothesis testing to assess whether the differences between insured and non-insured SMEs are statistically meaningful.

7.2 Hypothesis testing

Following the descriptive analysis, formal hypothesis tests are used to assess whether the differences observed between insured and non-insured SMEs are statistically significant. The testing procedure is divided into two parts. First, Welch's independent samples t-tests are applied to the numerical indicators of liquidity and payment default risk to compare group means. Second, a chi-square test of independence is used to examine whether blocked-account incidence is statistically associated with insurance status. These tests provide an initial statistical assessment of the two hypotheses before the regression models are estimated.

7.2.1 Independent samples t-tests

Welch's independent samples t-tests are used to compare the mean values of numerical liquidity and payment default risk indicators between insured and non-insured SMEs. This test is applied because it does not assume equal variances between the two groups, which makes it appropriate for comparing financial indicators that may differ in dispersion. Table 4 presents the t-test

results, including group means, mean differences, t-values, degrees of freedom, p-values, and statistical significance.

Table 4: Welch two-sample t-test results

Variable	Insured mean	Non-insured mean	Mean difference	t-value	df	p-value	Significance
Cash ratio	0.510	0.463	0.047	0.587	346.637	0.558	n.s.
Current ratio	2.643	2.202	0.441	2.101	346.349	0.036	*
Quick ratio	1.796	1.679	0.117	0.700	339.893	0.484	n.s.
NWC/TA	0.290	0.173	0.117	4.192	280.117	<0.001	***
DSO	67.106	85.002	-17.892	-2.541	250.892	0.012	*

*Note: Mean difference is calculated as insured mean minus non-insured mean. Statistical significance is denoted as follows: * p < 0.05; ** p < 0.01; *** p < 0.001; n.s. = not significant.*
Source: Own work based on Coface Slovenia data. (2026).

The results show statistically significant differences between insured and non-insured SMEs for the current ratio, NWC/TA, and DSO. For the current ratio, insured SMEs have a higher mean value than non-insured SMEs, with a mean difference of 0.441. This difference is statistically significant at the 5% level ($p = 0.036$), indicating that insured SMEs have, on average, a stronger current liquidity position than non-insured SMEs. For NWC/TA, the mean difference is also positive and statistically significant (mean difference = 0.117; $p < 0.001$), suggesting that insured SMEs have, on average, a stronger net working capital position relative to total assets.

By contrast, the differences in the cash ratio and quick ratio are not statistically significant ($p = 0.558$ and $p = 0.484$, respectively). Therefore, the results do not provide statistical evidence of differences between insured and non-insured SMEs for these narrower liquidity measures. The t-test results therefore provide partial support for H1, as statistically significant differences are found for the broader liquidity indicators, but not for all liquidity measures.

For payment default risk, the difference in DSO is negative and statistically significant (mean difference = -17.892; $p = 0.012$), indicating that insured SMEs have, on average, lower DSO than non-insured SMEs. Since lower DSO reflects faster receivables collection, this result suggests lower exposure to payment delays among insured firms. The t-test results therefore provide support for H2 with respect to receivables collection efficiency, as measured by DSO. However, DSO captures only one dimension of payment default risk. Since blocked-account incidence is a categorical outcome, the next step examines whether the occurrence of account

blockage is associated with insurance status using a chi-square test of independence before being examined further in the regression stage using a logistic model**.**

7.2.2 Chi-square test for blocked-account incidence

The next step in the analysis is to examine whether blocked-account incidence differs between insured and non-insured SMEs. Since this indicator is a categorical variable, a chi-square test of independence is used to assess whether there is a statistically significant association between insurance status and account blockage. Table 5 presents the observed and expected frequencies for insured and non-insured SMEs, together with the standardised residuals and the chi-square test output.

Table 5: Chi-square test for blocked-account incidence by insurance status

Insurance status	**Blocked-account incidence**	**Observed frequency**	**Expected frequency**	**Standardised residual**
Insured	No	224	207.87	4.99
Insured	Yes	14	30.13	-4.99
Non-insured	No	121	137.13	-4.99
Non-insured	Yes	36	19.87	4.99
Test output	$\chi^2 = 24.866$; df = 1; $p < 0.001$; OR = 0.210			

Note: Expected frequencies are calculated under the assumption of independence between insurance status and blocked-account incidence. Standardised residuals indicate whether observed frequencies are higher or lower than expected. OR = odds ratio.
Source: Own work based on Coface Slovenia data. (2026).

The chi-square test indicates a statistically significant association between insurance status and blocked-account incidence, χ^2 (1) = 24.866, $p < 0.001$. The observed frequencies show that 14 insured SMEs experienced account blockage, compared with an expected frequency of 30.13 under the assumption of independence. In contrast, 36 non-insured SMEs experienced account blockage, compared with an expected frequency of 19.87. This indicates that account blockage occurred less frequently than expected among insured SMEs and more frequently than expected among non-insured SMEs.

The standardised residuals confirm this pattern. The residual for insured SMEs with blocked accounts is negative (-4.99), while the residual for non-insured SMEs with blocked accounts is positive (4.99), showing that these cells contribute substantially to the overall chi-square result. In proportional terms, blocked-account incidence is lower among insured SMEs than among non-insured SMEs: 14 out of 238 insured SMEs (5.9%) experienced account blockage, compared with 36 out of 157 non-insured SMEs (22.9%).

The odds ratio of 0.210 indicates that the odds of blocked-account incidence among insured SMEs are substantially lower than among non-insured SMEs. More specifically, insured SMEs have approximately 79% lower odds of account blockage relative to non-insured SMEs. This result provides statistical support for H2, suggesting that SMEs covered by TCI are less exposed to severe payment-related financial distress, as measured by blocked-account incidence. As with the other results, this finding should be interpreted as evidence of association rather than causality.

7.3 Regression models

Following the hypothesis testing section, regression models are estimated to examine whether insurance status remains associated with the selected liquidity and payment default risk indicators after accounting for firm size and industry sector. This is important because observed group differences may partly reflect firm-level and sectoral characteristics rather than insurance status alone.

The regression analysis is organised according to the type of dependent variable and the corresponding estimation method. First, OLS regression models are estimated for the continuous dependent variables. These include the four liquidity indicators related to H1, namely the cash ratio, current ratio, quick ratio, and NWC/TA, as well as DSO, which is the continuous payment default risk indicator related to H2. Second, logistic regression is applied to blocked-account incidence, since this variable is binary and captures whether the firm experienced account blockage during the observed period. In all models, insurance status is the main explanatory variable, while firm size and industry sector are included as categorical control variables.

This structure separates the regression analysis by estimation method while preserving the conceptual distinction between the two hypotheses. The OLS models provide evidence for H1 through the liquidity indicators and for one part of H2 through DSO, whereas the logistic model provides additional evidence for H2 through blocked-account incidence. Presenting the models in this order allows the analysis to first examine continuous financial outcomes and then turn to the binary measure of more severe payment-related distress.

7.3.1 OLS regression models

The OLS regression models examine whether insurance status remains associated with the continuous dependent variables after accounting for firm size and industry sector. These models are estimated for the liquidity indicators used to test H1, namely the cash ratio, current ratio, quick ratio, and NWC/TA, as well as for DSO, which captures the receivables collection dimension of payment default risk under H2. In each model, insurance status represents the main explanatory variable, while firm size and industry sector are included as categorical

control variables. Table 6 reports the OLS regression results for these continuous dependent variables.

Table 6: OLS regression results for continuous dependent variables

Variable	Cash ratio	Current ratio	Quick ratio	NWC/TA	DSO
Insurance status: Insured	0.099 (0.084)	0.521* (0.219)	0.236 (0.172)	0.141*** (0.027)	-15.372* (6.720)
Firm size: Small	-0.177 (0.098)	-0.505* (0.254)	-0.445 (0.200)	-0.066* (0.032)	-31.835*** (7.790)
Firm size: Medium	-0.339** (0.104)	-0.702* (0.271)	-0.780*** (0.214)	-0.111** (0.034)	-28.263*** (8.323)
Industry sector: Construction	-0.086 (0.116)	0.001 (0.302)	-0.006 (0.238)	0.025 (0.038)	-12.290 (9.281)
Industry sector: Commercial and services	0.235* (0.114)	0.844** (0.295)	0.519* (0.233)	0.077* (0.037)	-2.947 (9.065)
Industry sector: Process / consumer manufacturing and agro	-0.017 (0.102)	0.144 (0.266)	0.009 (0.210)	-0.023 (0.033)	6.736 (8.177)
Observations	395	395	395	395	395
R^2	0.054	0.061	0.060	0.101	0.072
Adjusted R^2	0.039	0.046	0.046	0.087	0.057
F-statistic	3.690	4.167	4.138	7.238	4.994
Model p-value	0.001	<0.001	<0.001	<0.001	<0.001

*Note: Standard errors are reported in parentheses. Values are rounded to three decimal places. The reference categories are non-insured SMEs, micro firms, and capital goods / transport-related manufacturing. Statistical significance is denoted as follows: *** p < 0.001, ** p < 0.01, * p < 0.05. Coefficients without significance stars are not statistically significant at the 5% level.*
Source: Own work based on Coface Slovenia data. (2026).

Table 6 shows that, with respect to H1, insurance status remains positively associated with the current ratio and NWC/TA after controlling for firm size and industry sector. In the current ratio model, the coefficient for insured SMEs is positive and statistically significant at the 5% level ($\beta = 0.521$; $p < 0.05$). This means that, holding firm size and industry sector constant, insured SMEs have, on average, a current ratio that is 0.521 points higher than the current ratio of non-insured SMEs. This indicates a stronger short-term liquidity position among insured firms when liquidity is measured through current assets relative to current liabilities. The association is also evident for NWC/TA. The coefficient for insured SMEs is positive and statistically significant at the 0.1% level ($\beta = 0.141$; $p < 0.001$). This means that, after accounting for firm size and industry sector, insured SMEs have, on average, an NWC/TA ratio that is 0.141 points higher than that of non-insured SMEs. Since NWC/TA is expressed as a ratio, this corresponds to a

higher net working capital position relative to total assets among insured SMEs.

By contrast, the coefficients for insurance status in the cash ratio and quick ratio models are positive but not statistically significant. This means that the regression results do not provide statistical evidence that insured and non-insured SMEs differ in these narrower liquidity measures after controlling for firm size and industry sector. The results therefore provide partial support for H1, as the positive association between TCI and liquidity is statistically significant for broader liquidity indicators, particularly the current ratio and NWC/TA, but not for all liquidity measures.

With respect to H2, the DSO model shows a negative and statistically significant coefficient for insured SMEs ($\beta = -15.372$; $p < 0.05$). This indicates that, after controlling for firm size and industry sector, insured SMEs have, on average, DSO that is approximately 15.4 days lower than that of non-insured SMEs. Since lower DSO reflects faster receivables collection, this result supports H2 with regard to receivables collection efficiency and lower exposure to payment delays among insured firms.

The control variables also provide useful insight into differences in the dependent variables across firm characteristics. Compared with micro enterprises, medium-sized SMEs have significantly lower values for all four liquidity measures and significantly lower DSO. The coefficient for medium-sized enterprises in the quick ratio model is -0.780 and statistically significant at the 0.1% level. This means that, holding insurance status and industry sector constant, medium-sized SMEs have, on average, a quick ratio that is 0.780 points lower than micro enterprises, which serve as the reference category. Medium-sized enterprises also have significantly lower cash ratio, current ratio, and NWC/TA values, suggesting lower liquidity across both narrow and broader measures. In the DSO model, the coefficient for medium-sized enterprises is also negative and statistically significant ($\beta = -28.263$; $p < 0.001$), indicating shorter receivables collection periods than among micro enterprises. Small enterprises show a more limited pattern. Compared with micro enterprises, they have significantly lower current ratio and NWC/TA values, while the differences in the cash ratio and quick ratio are not statistically significant. They also have significantly lower DSO ($\beta = -31.835$; $p < 0.001$), suggesting faster receivables collection compared with micro enterprises. This indicates that size-related differences are visible not only in liquidity outcomes, but also in receivables collection efficiency.

Relative to the reference sector, firms in the commercial and services sector have significantly higher liquidity values across all four liquidity models. The largest coefficient is observed in the current ratio model ($\beta = 0.844$; $p < 0.01$), indicating that, holding insurance status and firm size constant, firms in this sector have, on average, a current ratio that is 0.844 points higher than firms in the capital goods and transport-related manufacturing sector. Significant positive coefficients are also observed for the cash ratio, quick ratio, and NWC/TA, suggesting that the stronger liquidity position of commercial and services firms is consistent across both narrow

and broader liquidity measures. On the other hand, none of the industry-sector coefficients are statistically significant in the DSO model, indicating that DSO does not differ systematically across industry sectors after controlling for insurance status and firm size. The R^2 values range from 0.054 to 0.101 and adjusted R^2 from 0.039 to 0.087, while all five models are statistically significant ($p < 0.05$), although their explanatory power remains limited. However, the purpose of these models is not prediction, but to examine whether insurance status remains associated with the outcomes after controlling for firm size and industry sector.

These findings indicate that the relationship between insurance status and financial outcomes is not uniform across all indicators. The positive and statistically significant coefficients for the current ratio and NWC/TA indicate that TCI is more clearly associated with broader measures of short-term solvency and working capital position than with narrower liquidity indicators such as the cash ratio and quick ratio. At the same time, the negative and statistically significant coefficient for DSO indicates that insured SMEs are associated with faster receivables collection, which supports the receivables collection dimension of H2. This supports the inclusion of control variables in the regression models and indicates that the association between TCI and SME financial outcomes should be interpreted in the context of firm size and industry-sector differences. The next part of the analysis examines blocked-account incidence as a binary payment default risk outcome using logistic regression.

7.3.2 Logistic regression model for blocked accounts

The logistic regression model examines blocked-account incidence as the binary payment default risk outcome under H2. While DSO was analysed in the OLS regression models as a continuous indicator of receivables collection efficiency, blocked-account incidence captures a more severe form of payment-related financial distress. The dependent variable equals 1 if the firm had a blocked account during the observed period and 0 otherwise, which makes logistic regression the appropriate estimation method for this part of the analysis. The purpose of this model is to assess whether insurance status is associated with the likelihood of account blockage after controlling for firm size and industry sector. Insurance status is included as the main explanatory variable, while firm size and industry sector are included as categorical control variables.

The results are reported through logistic regression coefficients, z-values, p-values, odds ratios, and 95% confidence intervals (hereinafter: CI). In logistic regression, the coefficient indicates the direction of the association in log-odds terms, while the odds ratio provides a more intuitive interpretation of the magnitude of the association. An odds ratio below one indicates lower odds of account blockage relative to the reference category, while an odds ratio above one indicates higher odds. Unlike the OLS coefficients, the logistic regression estimates should not be interpreted as changes in the average value of the dependent variable. For this reason, the interpretation focuses primarily on odds ratios, which show how the odds of account blockage differ between insured and non-insured SMEs after the control variables are included.

Additional model performance measures are included to assess model fit and classification quality. McFadden R^2 is reported as a pseudo-R^2 measure, indicating the improvement in model fit compared with the null model. Since McFadden R^2 is not equivalent to the ordinary R^2 used in OLS regression, it is interpreted as an indicator of relative model fit rather than as the proportion of explained variance. The ROC curve and the area under the curve (hereinafter: AUC) are used to evaluate the model's ability to distinguish between firms with and without blocked accounts. The optimal classification threshold is identified using the Youden index, which selects the threshold that provides the best balance between sensitivity and specificity. Based on this threshold, accuracy, sensitivity, and specificity are reported as classification performance measures. Table 7 presents the logistic regression estimates and model performance results for blocked-account incidence.

Table 7: Logistic regression results and model performance for blocked-account incidence

Logistic regression estimates					
Variable	**Coefficient**	**z-value**	**p-value**	**Odds ratio**	**95% CI for odds ratio**
Insurance status: Insured	-1.363*** (0.353)	-3.859	<0.001	0.256	0.128–0.511
Firm size: Small	-1.473*** (0.421)	-3.497	<0.001	0.229	0.100–0.523
Firm size: Medium	-0.702 (0.397)	-1.767	0.077	0.495	0.227–1.079
Industry sector: Construction	0.366 (0.428)	0.854	0.393	1.442	0.623–3.338
Industry sector: Commercial and services	-0.074 (0.435)	-0.171	0.864	0.928	0.395–2.179
Industry sector: Process / consumer manufacturing and agro	-0.398 (0.491)	-0.811	0.417	0.672	0.257–1.758

Model fit and classification performance					
Observations	395	McFadden R^2	0.138	AUC	0.756
Optimal threshold	0.156	Accuracy	0.790	Sensitivity	0.620
Specificity	0.814	Null deviance	300.070	Residual deviance	258.620

*Note: The dependent variable equals 1 if the firm had a blocked account and 0 otherwise. Standard errors are reported in parentheses. Values are rounded to three decimal places. The reference categories are non-insured SMEs, micro firms, and capital goods / transport-related manufacturing. Accuracy, sensitivity, and specificity are calculated using the optimal threshold identified from the ROC curve based on the Youden index. Statistical significance is denoted as follows: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.*

Source: Own work based on Coface Slovenia data. (2026).

Table 7 shows that insurance status is significantly associated with blocked-account incidence after controlling for firm size and industry sector. The coefficient for insured SMEs is negative and statistically significant at the 0.1% level ($\beta = -1.363$; $p < 0.001$). The corresponding odds ratio is 0.256, with a 95% CI of 0.128–0.511. Since the odds ratio is below one and the confidence interval does not include one, this result indicates that insured SMEs have significantly lower odds of experiencing account blockage than non-insured SMEs, holding firm size and industry sector constant. More specifically, the odds of blocked-account incidence among insured SMEs are approximately 74.4% lower than among non-insured SMEs.

Firm size is also relevant in the logistic regression model. Compared with micro SMEs, small SMEs have significantly lower odds of blocked-account incidence ($\beta = -1.473$; $p < 0.001$; odds ratio = 0.229). This indicates that, after controlling for insurance status and industry sector, the odds of account blockage among small SMEs are approximately 77.1% lower than among micro SMEs. The remaining firm-size and industry-sector coefficients are not statistically significant at the 5% level, indicating that the model does not provide sufficient evidence of systematic differences in blocked-account incidence across these categories after controlling for insurance status and the other firm characteristics.

The model performance measures provide additional information on model fit and classification performance. The McFadden R^2 value of 0.138 indicates that the fitted logistic regression model provides a better fit than the null model. The AUC value of 0.756 indicates acceptable discriminatory ability, suggesting that the model is reasonably effective in distinguishing between firms that experienced account blockage and those that did not. The optimal classification threshold derived from the ROC curve is 0.156. This value is below the conventional threshold of 0.5, which is appropriate in this context because blocked-account incidence is relatively rare in the sample. A lower threshold makes the model more sensitive to firms with a higher risk of account blockage, rather than classifying most observations as non-blocked. Using the optimal threshold of 0.156, the model achieves an accuracy of 0.790, indicating that 79.0% of all observations are correctly classified. Sensitivity is 0.620, meaning that the model correctly identifies 62.0% of firms that experienced account blockage. Specificity is higher, at 0.814, indicating that the model correctly identifies 81.4% of firms without account blockage. This suggests that the model has stronger classification performance for non-blocked firms than for blocked firms. Nevertheless, the sensitivity value indicates that the model identifies a meaningful proportion of blocked-account cases, which is relevant given the relatively low incidence of account blockage in the sample.

These results provide strong support for H2 with respect to blocked-account incidence. Together with the OLS results for DSO, they indicate that TCI is associated with lower payment default risk across both dimensions examined in the regression analysis: faster receivables collection and a lower likelihood of account blockage. The evidence is therefore consistent with the view that insured SMEs are less exposed to payment-related difficulties than non-insured

SMEs, after accounting for firm size and industry sector. As with the other empirical results, these findings should be interpreted as evidence of association rather than causality.

7.4 Summary of findings

The empirical findings indicate that SMEs covered by TCI differ from non-insured SMEs in several relevant financial dimensions. However, the strength of the evidence varies across the examined indicators. The relationship between TCI and SME financial outcomes appears more pronounced for payment default risk than for liquidity, suggesting that the relevance of TCI is most clearly reflected in receivables collection efficiency and the occurrence of account blockage.

With respect to liquidity, the results provide partial support for H1. The descriptive statistics show that insured SMEs have higher average values across all four liquidity indicators. However, the hypothesis tests and regression models indicate that statistically significant differences are concentrated in broader liquidity measures. Insured SMEs have significantly higher current ratio and NWC/TA values than non-insured SMEs. After controlling for firm size and industry sector, the regression results confirm that insured SMEs maintain stronger broader liquidity positions than non-insured SMEs, particularly in relation to short-term solvency and net working capital position. By contrast, the cash ratio and quick ratio are not statistically significant in the regression models, which suggests that the association between TCI and liquidity is not consistent across all liquidity measures.

The evidence is stronger for payment default risk. Insured SMEs have significantly lower DSO than non-insured SMEs in both the hypothesis testing and regression analysis. The OLS regression results show that this relationship remains significant after accounting for firm size and industry sector, indicating more efficient receivables collection among insured firms and lower exposure to payment delays. The analysis of blocked-account incidence provides further support for this result. The chi-square test shows a statistically significant association between insurance status and account blockage, while the logistic regression confirms that this relationship remains significant after controlling for firm size and industry sector. The logistic regression results show that insured SMEs have substantially lower odds of experiencing account blockage than non-insured SMEs. The control variables further indicate that firm characteristics are relevant for explaining variation in the dependent variables. Firm size is associated with both liquidity and DSO, while industry sector is particularly relevant in the liquidity regressions. This confirms the importance of accounting for firm size and industry sector when examining the relationship between insurance status and financial outcomes.

Taken together, the results suggest that TCI is associated with more favourable financial outcomes among Slovenian SMEs, but the association is stronger for payment default risk than for liquidity. H1 is therefore only partially supported, as significant results are observed for the current ratio and NWC/TA but not for all liquidity indicators. H2 receives stronger support, particularly through lower DSO and lower blocked-account incidence among insured SMEs.

Since the dataset is observational, these findings should be interpreted as evidence of association rather than causal effects.

8 DISCUSSION

This chapter discusses the empirical findings in relation to the theoretical framework and the research hypotheses. It interprets the main results, explains their theoretical and practical implications, and outlines the main limitations of the study together with directions for future research.

8.1 Interpretation of the main findings

The empirical results suggest that the relationship between TCI and SME financial outcomes is more nuanced than a simple distinction between insured and non-insured firms. Insured SMEs generally display more favourable financial characteristics, but the strength of the association differs across the two dimensions examined in this thesis. The evidence is more consistent for payment default risk than for liquidity, indicating that TCI appears to be more closely linked to receivables management and payment-risk mitigation than to all aspects of short-term liquidity.

The liquidity results provide partial support for H1. The positive association between insurance status and the current ratio and NWC/TA suggests that SMEs covered by TCI display a stronger broader liquidity position than non-insured SMEs, after accounting for differences in firm size and industry sector. This finding is consistent with the view that TCI may contribute to financial stability by protecting trade receivables and reducing the potential liquidity shock caused by buyer non-payment (ICISA, 2015; Jus, 2004). However, the lack of statistical significance for the cash ratio and quick ratio indicates that this association should not be interpreted as evidence that insured SMEs necessarily hold more immediately available liquid assets. Rather, the results suggest that the liquidity relevance of TCI is more visible in broader measures of short-term solvency and working capital than in the narrowest liquidity indicators.

This interpretation is theoretically plausible because TCI does not directly increase cash holdings. Its primary function is not to create liquidity in the same way as bank financing or equity capital, but to reduce uncertainty around receivables and protect firms against losses from buyer insolvency or protracted default (ICISA, 2015). Through credit-limit decisions, buyer monitoring, and debt collection support, TCI may improve the management of trade receivables and reduce the probability that unpaid invoices develop into more serious financial pressure (Becue, 2013). Therefore, the partial support for H1 should not be interpreted as a weak result. Instead, it suggests that the liquidity effect of TCI is indirect and more likely to appear through working capital and current-asset-based indicators than through cash-based measures.

The results for payment default risk provide stronger support for H2. The lower DSO among insured SMEs indicates more efficient receivables collection, which is directly aligned with the theoretical mechanisms of TCI. The literature emphasises that firms selling on deferred payment terms face both non-payment risk and financing pressure, because receivables tie up capital until customers pay (Li et al., 2016). In this context, lower DSO among insured SMEs suggests that TCI may be associated with more effective receivables control and lower exposure to payment delays**.** This is consistent with the operational role of credit insurers, which includes buyer assessment, monitoring, credit-limit management, and collection support (Becue, 2013; ICISA, 2015).

The strongest empirical evidence is found for blocked-account incidence. The logistic regression results show that insured SMEs have substantially lower odds of experiencing account blockage than non-insured SMEs, after controlling for firm size and industry sector. This finding is important because account blockage represents a more severe form of payment-related financial distress than delayed receivables collection alone. It suggests that the association between TCI and payment default risk is not limited to ordinary collection efficiency but may also extend to lower exposure to serious financial disruption. This finding is consistent with policy and empirical evidence showing that late payments can generate liquidity pressure, threaten business continuity, and contribute to insolvency risk among SMEs (Ferrara & Ferraresi, 2022).

The findings also underline the relevance of controlling for firm size and industry sector. Differences in liquidity and payment behaviour are not explained by insurance status alone. Small and medium-sized SMEs have significantly lower DSO than micro SMEs, suggesting that receivables collection efficiency may differ within the SME segment itself. This can be interpreted in light of the broader literature on SME financing constraints, which suggests that smaller firms often face weaker bargaining power, more limited internal resources, and greater dependence on timely cash inflows (Bakhtiari et al., 2020). Industry sector also plays an important role, particularly in the liquidity regressions. The stronger liquidity indicators observed among commercial and services firms relative to the reference sector suggest that sector-specific working capital structures, payment cycles, and business models may influence firm-level liquidity outcomes.

The findings therefore suggest that the role of TCI among Slovenian SMEs is more specific than a general improvement in liquidity. Its relevance appears to be most clearly connected to payment-risk management, receivables collection efficiency, and reduced exposure to severe payment-related distress. However, given the observational nature of the dataset, these relationships should be interpreted as associations rather than causal effects.

8.2 Theoretical and practical implications

The findings contribute to understanding the role of TCI in SME financial resilience. From a theoretical perspective, the results support the view that TCI should not be understood only as

an indemnity-based product that compensates firms after buyer default, but as a broader risk management mechanism that combines receivables monitoring, credit-limit decisions, indemnification, and recovery support (ICISA, 2015; Becue, 2013).

The results also refine the theoretical link between TCI and liquidity. The partial support for the liquidity hypothesis suggests that TCI is not a direct liquidity-generating instrument. It does not increase cash holdings in the same way as a loan, equity injection, or other external financing source. Instead, its connection with liquidity appears to operate indirectly through the protection and management of receivables. This explains why the association is more visible in broader liquidity indicators, such as the current ratio and NWC/TA, than in narrow cash-based measures. For future research, this suggests that TCI should be analysed through specific financial channels rather than treated as a general liquidity solution.

The stronger evidence for payment default risk has an important implication for both theory and practice. The findings suggest that the most relevant channel through which TCI is associated with SME financial outcomes is payment-risk management. Lower DSO and lower blocked-account incidence among insured SMEs indicate that the practical value of TCI lies not only in compensation after default, but also in supporting more disciplined receivables management and reducing exposure to severe payment-related distress. This is consistent with the operational role of credit insurers, which includes buyer assessment, monitoring, credit-limit management, and debt collection support (ICISA, 2015).

For SMEs, this means that TCI should not be viewed merely as an insurance cost or as protection against exceptional buyer insolvency. It can also be understood as a tool that supports day-to-day credit management, improves visibility over buyer risk, and strengthens the firm's ability to manage receivables more systematically. This is especially relevant in an environment where delayed payments and liquidity pressure remain important business challenges for SMEs (Ferrara & Ferraresi, 2022; EISMEA, 2025). The findings suggest that SMEs may benefit most from TCI when it is integrated into their broader receivables management process, rather than treated as a passive policy that becomes relevant only when a claim occurs.

For trade credit insurers, the results highlight the importance of communicating the broader value of TCI to SME clients. The empirical evidence is particularly strong for payment default risk, as reflected in both receivables collection efficiency and blocked-account incidence. This suggests that insurers should emphasise services such as buyer monitoring, credit information, credit-limit management, early warning signals, and debt collection support. These functions may be especially valuable for SMEs because they address practical weaknesses in internal credit management capacity and support a more preventive approach to payment-risk management (Becue, 2013).

Finally, the findings may be relevant for financial institutions and policy discussions. Although this thesis does not directly examine access to finance, lower DSO and lower blocked-account incidence among insured SMEs suggest that insured firms may display a more favourable

payment-risk profile. This may be relevant for banks, factoring providers, and other stakeholders that assess the quality of receivables in short-term financing decisions. From a policy perspective, TCI cannot replace broader measures aimed at improving payment discipline, reducing late payments, or strengthening access to finance. However, it may form part of a wider framework for supporting SME resilience, particularly in economies where late payments and insolvency risks continue to affect business stability (Ferrara & Ferraresi, 2022).

8.3 Limitations and directions for future research

The interpretation of the findings is shaped by the research design and the available data. Since the study is based on observational firm-level data, the empirical analysis identifies associations rather than causal effects. Although the regression models control for firm size and industry sector, insured and non-insured SMEs may still differ in unobserved characteristics, such as credit-management quality, internal monitoring of receivables, financial discipline, export orientation, customer-portfolio risk, or management practices. These unobserved differences may partly explain the more favourable liquidity and payment-risk outcomes observed among insured firms. Therefore, the results should not be interpreted as evidence that TCI alone causes the observed differences between insured and non-insured SMEs.

Another important limitation concerns the construction of the benchmark group. The non-insured group consists of enterprises that used Coface debt collection services during the observed period but did not have active TCI coverage. This makes the comparison meaningful within the Coface Slovenia setting, as all firms in the sample had a documented commercial relationship with Coface. However, this group may not fully represent the wider population of non-insured SMEs in Slovenia. Firms using debt collection services may already be more exposed to payment collection problems than non-insured firms that did not require such services. As a result, part of the observed differences between insured and non-insured firms may reflect the specific characteristics of the benchmark group rather than insurance status alone.

The analysis is also limited by the available control variables. The regression models include firm size and industry sector, but they do not include other firm-level characteristics that may influence liquidity and payment behaviour. These may include profitability, leverage, firm age, sales growth, export orientation, customer concentration, buyer-portfolio quality, or the maturity of internal credit-management procedures. The absence of these variables means that the models cannot fully account for all structural differences between insured and non-insured SMEs. This is particularly relevant because firms that purchase TCI may already differ from non-insured firms in their risk awareness, receivables management practices, or exposure to domestic and export customers.

The measurement of payment default risk should also be interpreted with caution. DSO and blocked-account incidence provide useful firm-level proxies because they capture receivables collection efficiency and more severe payment-related financial distress. However, they do not

capture the full complexity of commercial payment risk. DSO may be influenced by agreed payment terms, sector-specific business practices, invoice structure, customer concentration, or the composition of the buyer portfolio. Similarly, blocked-account incidence captures whether a serious form of financial distress occurred, but it does not reflect all cases of late payment, disputed receivables, partial non-payment, or buyer default. Moreover, it measures the occurrence of account blockage, but not its duration, intensity, or legal complexity once it occurs.

The period of analysis is another relevant limitation. The empirical analysis covers 2022–2024 and uses average firm-level values over this three-year period. This improves comparability across firms and reduces the influence of temporary annual fluctuations, but it also obscures year-to-year changes in liquidity and payment behaviour. Although this thesis was prepared in 2026, the analysis could not include 2025 financial data because annual reports and the corresponding financial statement data for 2025 were not yet sufficiently available at the time of dataset construction. The observation period begins in 2022, as comparable data for non-insured SMEs were not available for the preceding years. Therefore, the period 2022–2024 represents the most recent complete period available for consistent analysis, but the results do not capture developments after 2024.

Some methodological choices should also be considered when interpreting the findings. Winsorising the liquidity ratios at the 1st and 99th percentiles reduces the influence of extreme observations and possible reporting anomalies, but it may also reduce the visibility of genuine variation among firms with very unusual financial positions. In addition, using average values over the observed period provides a stable firm-level picture, but it limits the ability of the analysis to identify whether liquidity or payment behaviour changed after the adoption of TCI. For this reason, the results should be understood as a comparison of insured and non-insured firms based on averaged firm-level data, rather than as a dynamic assessment of changes over time.

The scope of the study is also limited to one country and one institutional setting. The empirical analysis is based on a case study of Coface Slovenia and focuses exclusively on Slovenian SMEs. This provides a consistent and relevant context for examining the relationship between TCI, liquidity, and payment default risk, but it may limit the generalisability of the findings. Credit insurance markets, payment behaviour, insolvency procedures, and SME financing conditions may differ across countries and insurers. Therefore, the findings should be interpreted in relation to the specific institutional and market context of Slovenia and Coface's client environment.

Future research could address these limitations in several ways. First, future studies could use panel data to examine year-by-year changes in liquidity and payment behaviour and to assess whether firms improve after obtaining TCI coverage. This would allow researchers to move beyond a comparison of insured and non-insured firms and examine changes within firms over time. Second, additional firm-level controls, such as profitability, leverage, firm age, export orientation, customer concentration, sales growth, and buyer-portfolio risk, could be included to reduce omitted-variable bias and improve the comparability of insured and non-insured firms. Future studies could also apply methods such as propensity score matching or research designs based on credit-limit decisions. These approaches could help create more comparable groups of insured and non-insured firms and reduce the risk that the results are driven by selection bias or other endogeneity problems. Further research could also examine buyer-level data, credit-limit decisions, claims experience, overdue invoices, and recovery outcomes to better understand the mechanisms through which TCI may influence SME liquidity and payment default risk. Such data would make it possible to distinguish more clearly between the preventive, indemnification, and recovery functions of TCI.

Finally, extending the analysis to other countries, other credit insurers, or broader SME samples would help assess whether the findings from the Coface Slovenia case are also present in wider market settings. Comparative research across countries or insurers could provide additional insight into how institutional environments, payment cultures, and credit insurance market structures shape the relationship between TCI and SME financial resilience.

9 CONCLUSION

This thesis examined how TCI is associated with liquidity and payment default risk among Slovenian SMEs. The findings show that the role of TCI is not uniform across all financial indicators. Instead, its relevance is most clearly visible in the area where its mechanisms are most directly applied: the management of trade receivables and payment-related risk.

The liquidity results suggest a selective rather than general relationship. SMEs covered by TCI show stronger outcomes for broader liquidity measures, particularly the current ratio and NWC/TA, while the evidence is weaker for the cash ratio and quick ratio. This indicates that TCI should not be interpreted as an instrument that directly increases immediately available liquid assets. Rather, its link with liquidity appears to operate indirectly, through the protection of receivables and a more stable working capital position.

The evidence is stronger for payment default risk. Insured SMEs are associated with more efficient receivables collection and a lower likelihood of account blockage. These findings are consistent with the practical logic of TCI, which combines risk prevention, buyer monitoring, credit-limit discipline, debt collection support, and indemnification. In this sense, TCI is not only relevant after buyer default occurs, but also as part of a broader framework for identifying and managing payment risk before it develops into more serious financial distress.

Overall, the thesis contributes to a more precise understanding of TCI in the SME context. For Slovenian SMEs, TCI appears to be most relevant as a receivables-risk management mechanism rather than as a general liquidity solution. Its strongest contribution lies in supporting receivables discipline, reducing uncertainty around customer payments, and lowering exposure to severe payment-related distress. At the same time, the findings should be interpreted with caution, as the analysis identifies associations rather than causal effects. Nevertheless, the results provide firm-level evidence that SMEs covered by TCI differ from non-insured SMEs in financially meaningful ways, particularly in relation to payment default risk.

The thesis therefore concludes that TCI can support SME financial resilience, primarily through the management of trade receivables and payment risk. Its value lies less in uniformly improving all liquidity indicators and more in reducing one of the key vulnerabilities of SMEs: the risk that sales made on deferred payment terms are not converted into cash in a timely and reliable manner.

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APPENDIX

Appendix: R code used for empirical analysis

Link to R code: http://rpubs.com/anjailic/

---

title: "Master data"

author: "Anja Ilic"

date: "2026-05-09"

output: html_document

```{r setup, include=FALSE}

knitr::opts_chunk$set(echo = TRUE)

```

Research question: How is trade credit insurance associated with liquidity and payment default risk among small and medium-sized enterprises in Slovenia?

```{r}

#Loading packages

library(readxl)

library(dplyr)

library(tidyr)

library(broom)

library(knitr)

library(writexl)

```

```{r}

#Importing dataset
```

mydata <- read_excel("Master_Data_Final.xlsx")

```

Explanation of data set:

- unit of observation: a firm (SME)

- number of observations: 395

- number of variables: 10

- source: AJPES

```{r}

# Rename NWC/TA to avoid problems with slash in R

if ("NWC/TA" %in% names(mydata)) {

  mydata <- mydata %>%

    rename(NWC_TA = `NWC/TA`)

}

# Factoring variables

mydata$Insured <- factor(mydata$Insured,

  levels = c(1, 0),

  labels = c("Insured", "Non-insured")

)

mydata$Accounts_Blocked <- factor(mydata$Accounts_Blocked, levels =

c(0, 1),

  labels = c("No", "Yes")

)

mydata$Firm_Size <- factor(mydata$Firm_Size,

  levels = c("Micro", "Small", "Medium")

```
)

mydata$NACE_Aggregated <- trimws(mydata$NACE_Aggregated)

mydata$NACE_Aggregated <- factor(mydata$NACE_Aggregated,

levels = c(

    "Capital goods / transport-related manufacturing",

    "Construction",

    "Commercial and services",

    "Process / consumer manufacturing and agro"

)

)

Create a numeric blocked-account variable for logistic regression

mydata$Accounts_Blocked_Num <- ifelse(mydata$Accounts_Blocked == "Yes", 1, 0)

str(mydata)

summary(mydata)
```

```{r}

# Descriptive statistics by insurance status
#Cash ratio

mydata %>% group_by(Insured) %>% summarise( N = n(), Mean = mean(Cash_Ratio, na.rm = TRUE), Median = median(Cash_Ratio, na.rm = TRUE), SD = sd(Cash_Ratio, na.rm = TRUE), Min = min(Cash_Ratio, na.rm = TRUE), Max = max(Cash_Ratio, na.rm = TRUE) )

# Current ratio

mydata %>% group_by(Insured) %>% summarise( N = n(), Mean = mean(Current_Ratio, na.rm = TRUE), Median = median(Current_Ratio, na.rm = TRUE), SD = sd(Current_Ratio, na.rm = TRUE), Min = min(Current_Ratio, na.rm = TRUE), Max = max(Current_Ratio, na.rm = TRUE) )
```

Quick ratio

mydata %>% group_by(Insured) %>% summarise(N = n(), Mean = mean(Quick_Ratio, na.rm = TRUE), Median = median(Quick_Ratio, na.rm = TRUE), SD = sd(Quick_Ratio, na.rm = TRUE), Min = min(Quick_Ratio, na.rm = TRUE), Max = max(Quick_Ratio, na.rm = TRUE))

NWC/TA

mydata %>% group_by(Insured) %>% summarise(N = n(), Mean = mean(NWC_TA, na.rm = TRUE), Median = median(NWC_TA, na.rm = TRUE), SD = sd(NWC_TA, na.rm = TRUE), Min = min(NWC_TA, na.rm = TRUE), Max = max(NWC_TA, na.rm = TRUE))

DSO

mydata %>% group_by(Insured) %>% summarise(N = n(), Mean = mean(DSO, na.rm = TRUE), Median = median(DSO, na.rm = TRUE), SD = sd(DSO, na.rm = TRUE), Min = min(DSO, na.rm = TRUE), Max = max(DSO, na.rm = TRUE))

Blocked-account incidence by insurance status

table(mydata$Insured, mydata$Accounts_Blocked)

prop.table(table(mydata$Insured, mydata$Accounts_Blocked), margin = 1) * 100

Distribution of main explanatory variable

table(mydata$Insured)

prop.table(table(mydata$Insured)) * 100

# Distribution of control variable: firm size
table(mydata$Firm_Size)

prop.table(table(mydata$Firm_Size)) * 100

Distribution of control variable: industry sector

table(mydata$NACE_Aggregated)

prop.table(table(mydata$NACE_Aggregated)) * 100

```

```{r}

# Welch t-tests for numerical dependent variables

```
t_cash <- t.test(Cash_Ratio ~ Insured, data = mydata)

t_current <- t.test(Current_Ratio ~ Insured, data = mydata)

t_quick <- t.test(Quick_Ratio ~ Insured, data = mydata)

t_nwc <- t.test(NWC_TA ~ Insured, data = mydata)

t_dso <- t.test(DSO ~ Insured, data = mydata)

Show individual outputs

t_cash

t_current

t_quick

t_nwc

t_dso
```

```{r}
# Chi-square test: Insurance status vs blocked-account incidence

# Create clean variables for this test only

chi_data <- mydata %>%

  mutate(

    Insurance_status = case_when(

      as.character(Insured) == "1" ~ "Insured",

      as.character(Insured) == "0" ~ "Non-insured",

      as.character(Insured) == "Insured" ~ "Insured",

      as.character(Insured) == "Non-insured" ~ "Non-insured",

      TRUE ~ NA_character_
```

```
    ),
    Blocked_account = case_when(
      as.character(Accounts_Blocked) == "1" ~ "Yes",
      as.character(Accounts_Blocked) == "0" ~ "No",
      as.character(Accounts_Blocked) == "Yes" ~ "Yes",
      as.character(Accounts_Blocked) == "No" ~ "No",
      TRUE ~ NA_character_
    )
  ) %>%
  mutate(
    Insurance_status = factor(
      Insurance_status,
      levels = c("Insured", "Non-insured")
    ),
    Blocked_account = factor(
      Blocked_account,
      levels = c("No", "Yes")
    )
  )
# Observed frequencies
blocked_table <- table(chi_data$Insurance_status, chi_data$Blocked_account)
blocked_table
# Pearson chi-square test
chi_test <- chisq.test(blocked_table, correct = FALSE)
```

```
chi_test

# Expected frequencies

chi_test$expected

# Standardized residuals

chi_test$stdres

# Odds ratio: insured relative to non-insured

odds_ratio <- (blocked_table["Insured", "Yes"] / blocked_table["Insured", "No"]) /

(blocked_table["Non-insured", "Yes"] / blocked_table["Non-insured", "No"])

odds_ratio
```

```{r}
# Regression models with two control variables

# Reference category for insurance status: Non-insured

# Set reference categories

mydata$Insured <- factor(

  mydata$Insured,

  levels = c("Non-insured", "Insured")

)

mydata$Firm_Size <- factor(

  mydata$Firm_Size,

  levels = c("Micro", "Small", "Medium")

)

mydata$NACE_Aggregated <- factor(
```

```
  mydata$NACE_Aggregated,
  levels = c(
    "Capital goods / transport-related manufacturing",
    "Construction",
    "Commercial and services",
    "Process / consumer manufacturing and agro"
  )
)
```

```{r}
# OLS regression models for liquidity indicators
model_cash <- lm(Cash_Ratio ~ Insured + Firm_Size + NACE_Aggregated, data = mydata)
model_current <- lm(Current_Ratio ~ Insured + Firm_Size + NACE_Aggregated, data = mydata)
model_quick <- lm(Quick_Ratio ~ Insured + Firm_Size + NACE_Aggregated, data = mydata)
model_nwc <- lm(NWC_TA ~ Insured + Firm_Size + NACE_Aggregated, data = mydata)
model_dso <- lm(DSO ~ Insured + Firm_Size + NACE_Aggregated, data = mydata)
# Regression output for liquidity indicators
summary(model_cash)
summary(model_current)
summary(model_quick)
summary(model_nwc)
summary(model_dso)
# Tidy coefficient outputs for easier table preparation
```

```
tidy(model_cash)

tidy(model_current)

tidy(model_quick)

tidy(model_nwc)

tidy(model_dso)

# Model fit statistics for OLS models

glance(model_cash)

glance(model_current)

glance(model_quick)

glance(model_nwc)

glance(model_dso)
```

```{r}
# Logistic regression model for blocked-account incidence

model_blocked <- glm(

  Accounts_Blocked_Num ~ Insured + Firm_Size + NACE_Aggregated,

  data = mydata,

  family = binomial

)

summary(model_blocked)

# McFadden pseudo R-squared
mcfadden_r2 <- 1 - (model_blocked$deviance / model_blocked$null.deviance)
round(mcfadden_r2, 3)

# Odds ratios for logistic regression
```

```
exp(coef(model_blocked))

# Odds ratios with 95% confidence intervals

exp(cbind(

  Odds_Ratio = coef(model_blocked),

  confint.default(model_blocked)

))
```

```{r}
# Predicted probabilities from the logistic regression model

mydata$predicted_prob_blocked <- predict(model_blocked, type = "response")

# Check first few predicted probabilities

head(mydata$predicted_prob_blocked)
```

```{r}
library(pROC)

# ROC curve and AUC

roc_blocked <- roc(

  response = mydata$Accounts_Blocked_Num,

  predictor = mydata$predicted_prob_blocked,

  levels = c(0, 1),

  direction = "<"

)

# Area under the curve
```

```
auc_blocked <- auc(roc_blocked)

# Display AUC rounded to three decimals

round(auc_blocked, 3)
```

```{r}
# Plot ROC curve

plot(

roc_blocked,

  main = "ROC curve for blocked-account incidence model"

)
```
```{r}
# Optimal threshold based on Youden index

optimal_coords <- coords(

  roc_blocked,

  x = "best",

  best.method = "youden",

  ret = c("threshold", "sensitivity", "specificity"),

  transpose = FALSE

)

optimal_coords

# Save optimal threshold

threshold_best <- optimal_coords$threshold

threshold_best
```

```

```{r}

# Predicted class using optimal threshold

mydata$predicted_class_best <- ifelse(

mydata$predicted_prob_blocked >= threshold_best,

1,

  0

)

```

```{r}
# Confusion matrix using optimal threshold

conf_matrix_best <- table(

  Actual = factor(mydata$Accounts_Blocked_Num, levels = c(0, 1)),

  Predicted = factor(mydata$predicted_class_best, levels = c(0, 1))

)

conf_matrix_best

```

```{r}

# Extract values from confusion matrix

TN <- conf_matrix_best["0", "0"]

FP <- conf_matrix_best["0", "1"]

FN <- conf_matrix_best["1", "0"]

TP <- conf_matrix_best["1", "1"]

# Accuracy, sensitivity and specificity

```
accuracy_best <- (TP + TN) / sum(conf_matrix_best)

sensitivity_best <- TP / (TP + FN)

specificity_best <- TN / (TN + FP)

Display rounded results

round(accuracy_best, 3)

round(sensitivity_best, 3)

round(specificity_best, 3)
```

```{r}
# Logistic regression model performance table

logit_performance <- data.frame(

  Measure = c(

    "McFadden R-squared",

    "AUC",

    "Optimal threshold",

    "Accuracy",

    "Sensitivity",

    "Specificity"

  ),

  Value = round(c(

    mcfadden_r2,

    as.numeric(auc_blocked),

    threshold_best,
```

```
    accuracy_best,
    sensitivity_best,
    specificity_best
  ), 3)
)
logit_performance
```