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Examining the Links Between Firm Performance and Insolvency

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Abstract

Assessing insolvency dynamics is essential for evaluating the financial health of non-financial corporations and mitigating macroeconomic and financial stability risks. This study leverages a newly created Statistics Canada dataset linking insolvency records with firm-level financial data to develop a robust framework for monitoring insolvency risk. We employ two complementary approaches: a univariate threshold method that establishes critical financial ratio benchmarks and a multivariate econometric model that accounts for interactions among financial indicators. These methods produce debt-at-risk measures that enhance risk assessment by combining simplicity with analytical depth. Finally, we apply these metrics to timely firm-level data, enabling continual monitoring of financial vulnerabilities.

Topics: Credit and credit aggregates, Econometric and statistical methods, Financial stability, Firm dynamics
JEL codes: D22, G33, L20

Résumé

L'évaluation de la dynamique des facteurs d'insolvabilité est essentielle pour jauger la santé financière des sociétés non financières et atténuer les risques pour la stabilité macroéconomique et financière. Cette étude permet de construire un cadre robuste pour surveiller le risque d'insolvabilité. Elle s'appuie sur un nouveau jeu de données créé par Statistique Canada qui met en relation dossiers d'insolvabilité et données financières désagrégées des entreprises. Nous exploitons deux approches complémentaires. Une méthode univariée par seuils, qui établit des repères critiques indépendamment pour chaque indicateur financier, et un modèle économétrique multivarié tenant compte des interactions entre les indicateurs financiers. Ces méthodes conduisent à des mesures de la dette exposée au risque qui allient la simplicité à la profondeur de l'analyse. Enfin, nous appliquons les mesures obtenues aux données plus fréquentes sur les entreprises, de manière à assurer une surveillance continue des vulnérabilités financières.

Sujets : Crédit et agrégats du crédit; Méthodes économétriques et statistiques; Stabilité financière; Dynamique des entreprises
Codes JEL : D22, G33, L20

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1. Introduction

Assessing insolvency dynamics is critical to evaluating the overall health of the business sector. A rise in insolvencies can pose macroeconomic risks, such as job losses, or financial stability concerns, including increased loan losses for banks. Accurately identifying firms at risk of insolvency requires access to timely firm-level data, such as the Quarterly Survey of Financial Statistics (QSFS), to ensure up-to-date assessments.

Moreover, developing insolvency risk metrics at the firm level is crucial because sectoral aggregate statistics often exhibit limited variation, making prediction more challenging. Since economic shocks impact firms in heterogeneous ways, relying solely on aggregate data fails to capture significant firm-level differences.

To address these challenges, this study leverages a newly created Statistics Canada dataset that links insolvency data from the Office of the Superintendent of Bankruptcy (OSB) with firm-level financial data from the National Accounts Longitudinal Microdata File (NALMF). This linked dataset allows for a detailed examination of the relationship between individual firms' financial characteristics and their likelihood of insolvency.

To develop a robust framework for monitoring and quantifying insolvency risk in the business sector, we construct a set of timely monitoring indicators using two complementary approaches. Our methodology consists of three key steps:

1. Univariate threshold approach – In the first step, we establish critical univariate thresholds for key financial ratios to identify firms at heightened insolvency risk. This involves analyzing the relationship between various lagged financial ratios and firm insolvency rates. Specifically, for each industry, we divide financial ratios into deciles and compute the insolvency rate within each bin. We then determine thresholds based on percentile distributions of financial ratios across industries. For example, we identify a debt ratio above the 70th percentile as a critical level, beyond which insolvency rates increase significantly.

2. Econometric model for multivariate thresholds – In the second step, we employ an econometric approach to infer multivariate risk thresholds. Using a logit model, we estimate the probability that a firm will file for insolvency,

accounting for interactions among different financial ratios. This enables a more comprehensive risk assessment that distinguishes between firms with different financial profiles—for example, we compare firms with low leverage and high liquidity to those with high leverage and low liquidity.

3. Application to timely microdata – We apply the thresholds identified in step 1 and the elasticities computed in step 2 to timely firm-level financial data (i.e., the QSFS microdata) for monitoring financial vulnerabilities in the business sector. We calculate two debt-at-risk measures, defined as the share of liabilities held by firms identified as the most vulnerable.

The univariate threshold approach of step 1 offers clearly defined critical thresholds that can be easily applied across different datasets, making it a practical tool for comparative analysis. Meanwhile, the multivariate econometric model in step 2 provides a more nuanced, probabilistic insolvency assessment by accounting for the interactions among financial ratios, allowing for a deeper understanding of firm-level vulnerabilities. Together, these approaches enhance the robustness of insolvency risk monitoring by balancing simplicity with analytical depth.

Section 2 provides an overview of the data used in this study, detailing the sources and characteristics of the QSFS microdata and the linked dataset from Statistics Canada. Section 3 explores the empirical relationships between financial ratios and insolvency risk, while Section 4 delves deeper into the logit model framework, including the interaction of financial ratios and other firm characteristics. Finally, Section 5 discusses the application of these methods to timely microdata, focusing on the integration of results into non-financial corporate monitoring.

2. Data

The OSB dataset contains annual information on which firms (anonymized) file for bankruptcy, file a bankruptcy proposal or go into receivership.[1] Our available sample runs from 2000 to 2023, though data before 2006 is more sparse.

The NALMF dataset runs from 2000 to 2022 and contains annual balance sheet and income statement items from all firms (anonymized) that file a tax return in Canada (roughly 1.4 million per year). It also has information on which North

[1] Business bankruptcies are the most frequent type of insolvency filing. The 2010–2019 monthly average is 256 compared with 85 for proposals.

American Industry Classification System (NAICS) industry group each firm belongs to.

We then merge the two datasets using a common firm identifier, though the actual firms remain anonymized. By merging the NALMF data with the OSB insolvency dataset, we gain a more comprehensive perspective on business dynamics. This integrated approach provides a significant advantage over earlier studies on Canadian business insolvencies, such as Baldwin et al. (1997) and Lecavalier (2006). These studies are limited by selection bias due to their sole focus on bankruptcies.

Chart 1: Total insolvencies: microdata versus data on the OSB website

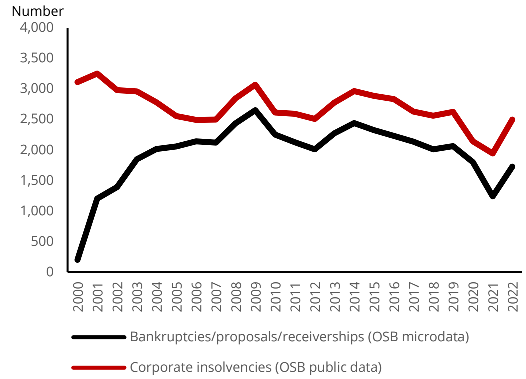
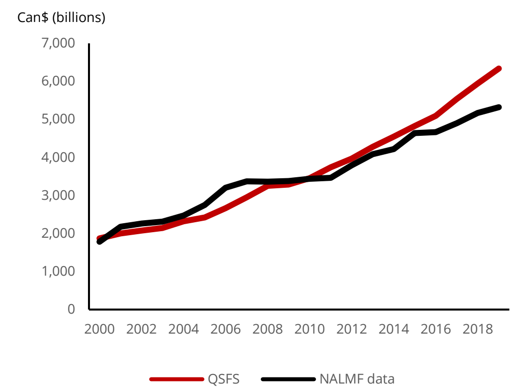


Chart 2: Comparison of total assets: QSFS versus NALMF data



Note: OSB is the Office of the Superintendent of Bankruptcy. NALMF is Statistics Canada's National Accounts Longitudinal Microdata File, and QSFS is its Quarterly Survey of Financial Statistics. A Statistics Canada dataset merges insolvency data from the OSB with firm-level financial data from the NALMF. This data is compared with aggregate data from the QSFS.
Sources: Statistics Canada and Bank of Canada calculations.
Last Observations: 2022 (Chart 1); 2019 (Chart 2)

Chart 1 and **Chart 2** compare the microdata with publicly available aggregates. Overall, the match is quite good.[2] For the OSB microdata, we sum business bankruptcies, proposals and receiverships and compare this with total annual corporate insolvencies published on the OSB website.[3] The trends match closely after 2006 but diverge significantly before that date due to the sparseness of the microdata. We compare the sum of the total assets per year of all firms in the

[2] The NALMF data consist of actual administrative data from all businesses that file taxes in Canada. By contrast, the QSFS is a survey based on a sample of medium and large firms. The final aggregates are derived from a combination of the survey responses, other data sources and estimation. As a result, discrepancies are to be expected, especially when we drill down to the industry level. QSFS data comparisons end in 2019 as there was a survey break in 2020.

[3] https://ised-isde.canada.ca/site/office-superintendent-bankruptcy/en/statistics-and-research

NALMF data with the total assets of non-financial corporations in the QSFS data (using the fourth quarter value as the annual value). The two series match fairly closely in terms of level, with some slight deviations in the trend toward the end of the sample. When we break down into industry groups based roughly on a two-digit NAICS classification, the fit deteriorates slightly for some industries but remains close.[4]

Our main variable of interest from the OSB data is firm insolvency, which we define as when a firm either (1) files for bankruptcy or (2) files an insolvency proposal or goes into receivership. The date for the insolvency is defined as the year in which a business files for insolvency.

In the NALMF data, we construct financial ratios for each of the main pillars of financial health: profitability (profit margin), liquidity (current ratio) and leverage (debt ratio).[5] We also look at the interest coverage ratio (ICR), which serves as an indicator of both profitability and leverage since it measures how many times income can cover debt obligations.[6]

2-1. Exit and insolvency rates over time

Insolvency and firm exit are two different concepts because a firm can exit for voluntary reasons without being insolvent. A business is defined as an exit in year *t* if it exists in the data in year t – 1 and is missing in year t. In addition, if the business has employees in year t – 1 but no employees in years t and t +1, it is defined as an exit in year t.[7] In cases where a business files for insolvency and exits shortly after in the same year, the business is classified as insolvent rather than simply an exit.[8]

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[4] See **Table A-1** in **Appendix A** for the components of each industry group.

[5] A large body of literature links corporate financial health to three broad categories of financial ratios: profitability, liquidity and leverage (Altman 1983; Scott 1981; Ohlson 1980; Bunn and Redwood 2003; and Vlieghe 2001).

[6] Profit margin is defined as earnings before interest, taxes, depreciation and amortization (EBITDA)/revenue; the current ratio is near-term assets/near-term liabilities; the debt ratio is liabilities/assets and the interest coverage ratio is EBITDA/interest expense.

[7] Employment is based on the average monthly employment from the payroll statement of account for current source deductions (PD7) or the T4 individual labour units if PD7 information is missing.

[8] This classification allows us to better identify differences between firms that become insolvent and those that do not. Because many businesses that file for insolvency in some form often exit, counting them as exits would further reduce the already small sample of insolvent firms and restrict our ability to identify relationships between firms' financial health and future financial distress.

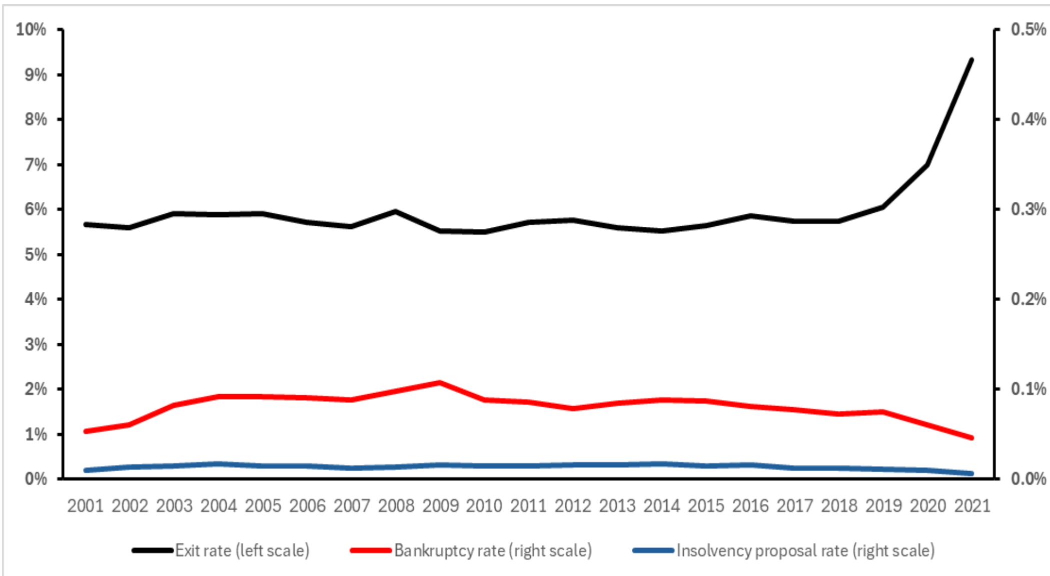
Chart 3 compares exit and insolvency rates over a 22-year period. The category of business exits is broader, encompassing various reasons beyond financial distress. Consequently, far fewer businesses file for insolvency compared with those that exit. Between 2001 and 2021, an average of 0.08% of businesses filed for bankruptcy and 0.01% submitted proposals annually, compared with 6% of businesses that exited each year.

While this note focuses on insolvency as a clear indicator of financial distress, it is important to acknowledge that not all firm exits occur through formal insolvency procedures. Some distressed firms may exit the market without undergoing insolvency yet still experience significant financial stress, leading to lender losses and layoffs. These factors are crucial for financial stability assessments since they highlight the broader economic implications of firm exits beyond formal insolvencies.

While we present some model estimation results related to exits in **Appendix B**, future research should further distinguish between "good" and "bad" exits to better understand their respective impacts on financial stability.[9]

[9] Some exits may also be voluntary. For example, as shown by Duprey et al. (2023), during the COVID-19 pandemic restrictions many businesses did not exit but only temporarily closed and reopened after restrictions were eased. These temporary exits might be "good" in the sense that they could support employment by preventing productive businesses from permanently exiting.

Chart 3: Rates of exits, bankruptcies and insolvency proposals



Note: A Statistics Canada dataset merges firm-level financial data from its National Accounts Longitudinal Microdata File with insolvency data from the Office of the Superintendent of Bankruptcy.
Sources: Statistics Canada and Bank of Canada calculations
Last Observation: 2021

Insolvency rates rose during the 2008–09 global financial crisis but have generally declined since 2009, with further decreases observed in 2020 and 2021. In contrast, exit rates in 2020 and 2021 reached historic highs during the examined period. In our sample, the exit rate remains stable until 2014, before substantially increasing during the COVID-19 pandemic, culminating in a historical peak in 2021. Lafrance-Cooke and McDougall (2023) show that the increase in the exit rate in 2020 is entirely attributable to small businesses.

2-2. Transition dynamics across business groups

Table 1 presents the relationship between businesses that were continuers, or that filed for bankruptcy or proposal/receivership, in year *t* and their status in the following year (*t* + 1) between 2001 and 2021. More than 93% of active firms remained active in the following year. The remainder of businesses exited (6.46%) or filed for bankruptcy (0.09%) or insolvency (0.01%). In addition, 96.08% of bankruptcies became exits in the year following the bankruptcy.[10] Similar to Lafrance-Cooke and McDougall (2023), there are three main messages from this transition table:

- most businesses that exit each year do so via non-bankruptcy pathways (first row)
- the majority of the bankrupt firms exit in the next year (second row)
- financially distressed businesses can often avoid exit and bankruptcy with an insolvency proposal, which is designed to help ensure a business's continuity (third row)

Table 1: Transitional matrix between business dynamics groups from 2001 to 2021 (%)

Year t	Year $t+1$				
	Active	Exit	Bankrupt	Proposal/receivership	Total
	Percent				
Active	93.43	6.46	0.09	0.01	100
Bankrupt	3.92	96.08	---	---	100
Proposal/receivership	79.70	9.40	10.90	---	100

Note: A Statistics Canada dataset merges firm-level financial data from its National Accounts Longitudinal Microdata File with insolvency data from the Office of the Superintendent of Bankruptcy.
Sources: Statistics Canada and Bank of Canada calculations

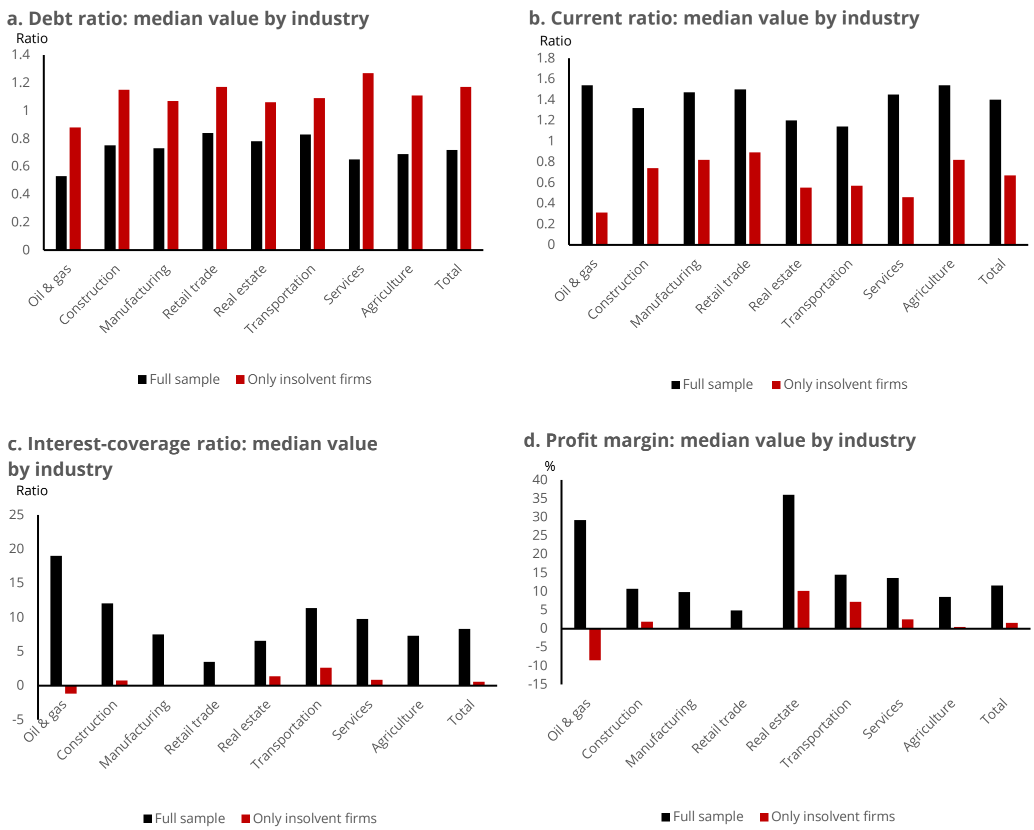
Previous work shows that the COVID-19 pandemic had a very uneven impact on firms (Grieder et al. 2021). Disentangling the effects of government support programs is outside the scope of available data. As a result, in our analysis in the subsequent sections we restrict the sample to 2019 and earlier to avoid the significant anomalies in the data attributable to the pandemic.

[10] As noted in Lafrance-Cooke and McDougall (2023), the 3.92% of bankrupt firms that remain active in the next year may be attributable to late tax filers that are still being captured in the dataset as having employment in the year following bankruptcy.

3. Empirical relationships between financial ratios and insolvency

Unsurprisingly, overall, we find that insolvent firms tend to have noticeably worse financial ratios from the previous year. These one-year lagged ratios vary by industry, indicating that different industries have different typical financial structures (**Chart 4**). As highlighted by Fortier-Labonté (2021), corporations filing for insolvency often underperform their industry peers in key metrics such as liquidity and leverage.

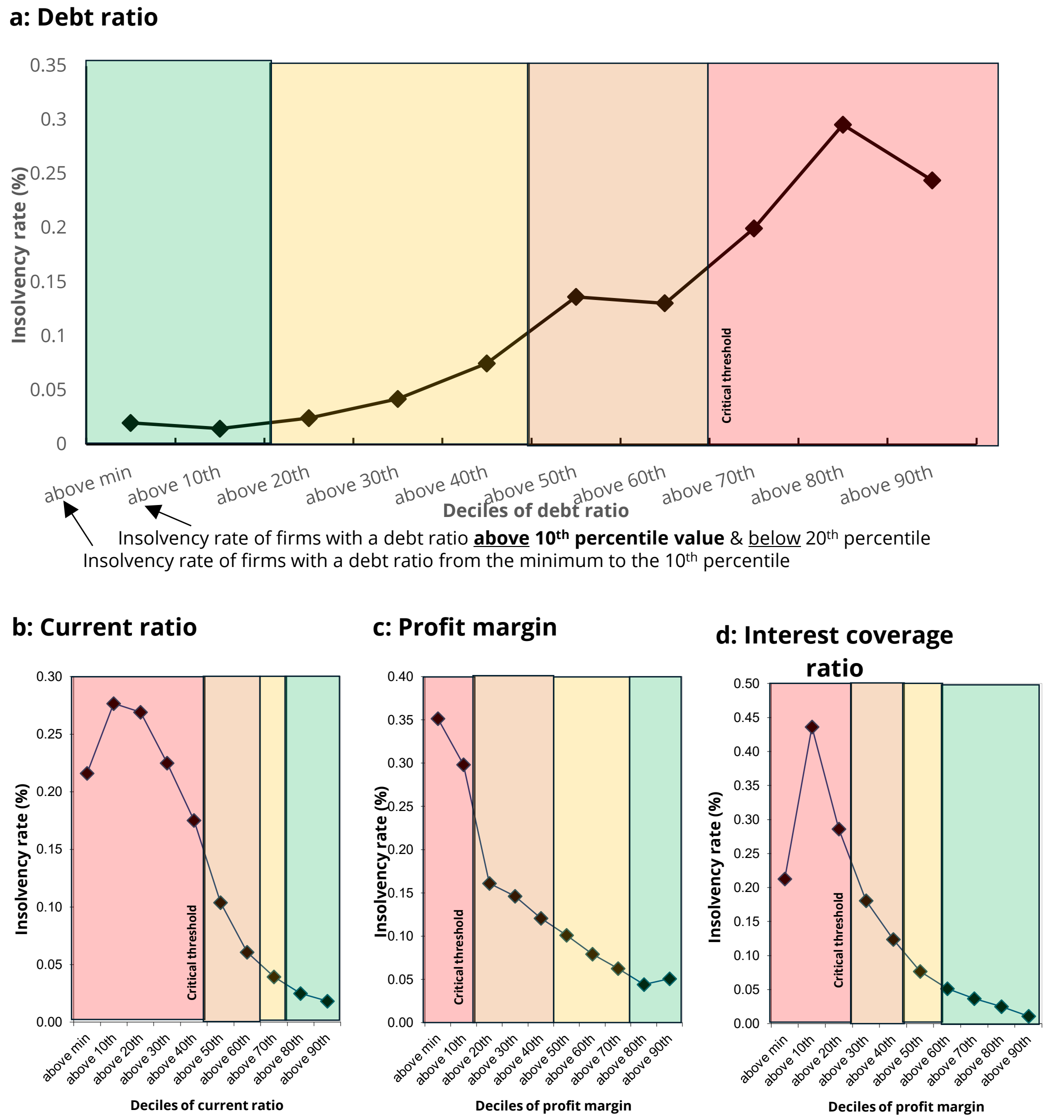
Chart 4: Median financial ratio by industry



Note: A Statistics Canada dataset merges firm-level financial data from its National Accounts Longitudinal Microdata File with insolvency data from the Office of the Superintendent of Bankruptcy.
Sources: Statistics Canada and Bank of Canada calculations

For each industry, we split the financial ratio into deciles and calculate the insolvency rate of firms within each bin. We find that the relationship between key financial ratios and insolvency tends to be nonlinear, allowing us to find clear risk thresholds. **Chart 5**, panel a illustrates this exercise using the debt ratio for the total non-financial sector. **Chart 5**, panel b; **Chart 5**, panel c and **Chart 5**, panel d show the results for the current ratio, profit margin and ICR, respectively.

Chart 5: The relationship between key financial ratios and insolvency tends to be nonlinear, allowing for clear risk thresholds



Note: In each panel, the green region represents where financial ratios are consistent with low insolvency rates (often approaching zero); the yellow region shows where insolvency rates begin to rise but generally remain quite low; the orange region shows where insolvency rates begin to rise more rapidly, and the red region shows where insolvency rates spike as the financial ratio's value deteriorates. The diamonds represent the insolvency rate of firms within each decile. A Statistics Canada dataset merges firm-level financial data from its National Accounts Longitudinal Microdata File with insolvency data from the Office of the Superintendent of Bankruptcy.

Sources: Statistics Canada and Bank of Canada calculations

The horizontal axis represents the deciles of each ratio, while the vertical axis is the insolvency rate. Thus, the diamonds represent the insolvency rate of firms within each decile. Across these financial ratios, we unsurprisingly find that insolvency rates are lowest among firms with relatively better financial ratios and highest for firms with weaker ones.

To generalize, the panels in **Chart 5** divide the insolvency rates into four regions:

- a green region where the financial ratios are consistent with low insolvency rates (often approaching zero)
- a yellow region where insolvency rates begin to rise but generally remain quite low
- an orange region where insolvency rates begin to rise more rapidly
- a red region where insolvency rates spike as the financial ratio's value deteriorates

We use the boundary between the orange and red regions as the critical threshold to identify firms most at risk. While **Chart 5** shows the financial ratios for the total non-financial sector, we also conduct this exercise by industry and select our thresholds so they are consistent across most industries. Importantly, we identify thresholds based on the percentile rather than a specific value to account for the heterogeneity in the distribution of financial ratios across industries. This allows us to better account for the differences in the financial structures of companies in different industries.

This section outlines the univariate thresholds for key financial ratios, as shown in **Chart 5**. In the following section, we extend the analysis by employing a multivariate econometric model to estimate insolvency probabilities while accounting for multiple firm characteristics. In Section 5, we apply both univariate and multivariate metrics to calculate the debt at risk.

4. Digging deeper using a logit model framework

In this section, we use a logit model to investigate which financial ratios—and combinations of ratios—are most significant in predicting future insolvencies.

Similar to Section 3, the model uses the sample between 2000 and 2019.[11] We estimate a multinomial logit model structured as follows:

$$\boldsymbol{Status_{i,t}} = \sum_{f,q,s} \boldsymbol{\beta_{fqs}} * \boldsymbol{FR^{fq}_{i,t-s}} + \sum_{\substack{f,k,q,s \\ (k \neq f)}} \boldsymbol{\beta_{fkqs}} * \boldsymbol{FR^{fq}_{i,t-s}} * \boldsymbol{FR^{kq}_{i,t-s}} + \boldsymbol{\gamma X_{i,t-1}} + \boldsymbol{\xi Y_{t,t-1,t-2}} + \boldsymbol{\alpha_j} + \boldsymbol{\varepsilon_{i,t}},$$

where the outcome variable $\boldsymbol{Status_{i,t}}$ represents one of three possible values: active business, exit or insolvency filing (including bankruptcy, insolvency proposal or receivership). The explanatory variables include the lagged values of key financial ratios listed above (debt ratio, ICR, current ratio and profit margins), categorized into quartiles within each industry, where $\boldsymbol{FR^{fq}_{i,t-s}}$ represents the quartile of financial ratio *f* for firm *i* in year *t*–*s* and $\boldsymbol{\beta_{fqs}}$ denotes the associated coefficient for quartile *q*.[12] Based on model fitness, we select two lags of financial ratios for the estimation. The model also includes interactions between the key financial ratios (i.e., $\boldsymbol{FR^{fq}_{i,t-s}} * \boldsymbol{FR^{kq}_{i,t-s}}$), enabling us to better understand under which circumstances each ratio becomes an important signal of distress.

Controls include macroeconomic indicators ($\mathbf{Y}$) such as growth in gross domestic product and growth in the consumer price index (in year *t* and two lags), and firm-specific characteristics ($\boldsymbol{X_i}$) including categories of size, age, quartiles of labour productivity and total assets (all measured in $t-1$). The fixed effects ($\boldsymbol{\alpha_j}$) capture time-invariant characteristics at the industry levels.

Chart 6 illustrates the average probability of insolvency across quartiles of four key financial ratios based on the multinomial logit regression.[13] The plotted points represent the mean probability of insolvency within each category, while the vertical bars denote confidence intervals.

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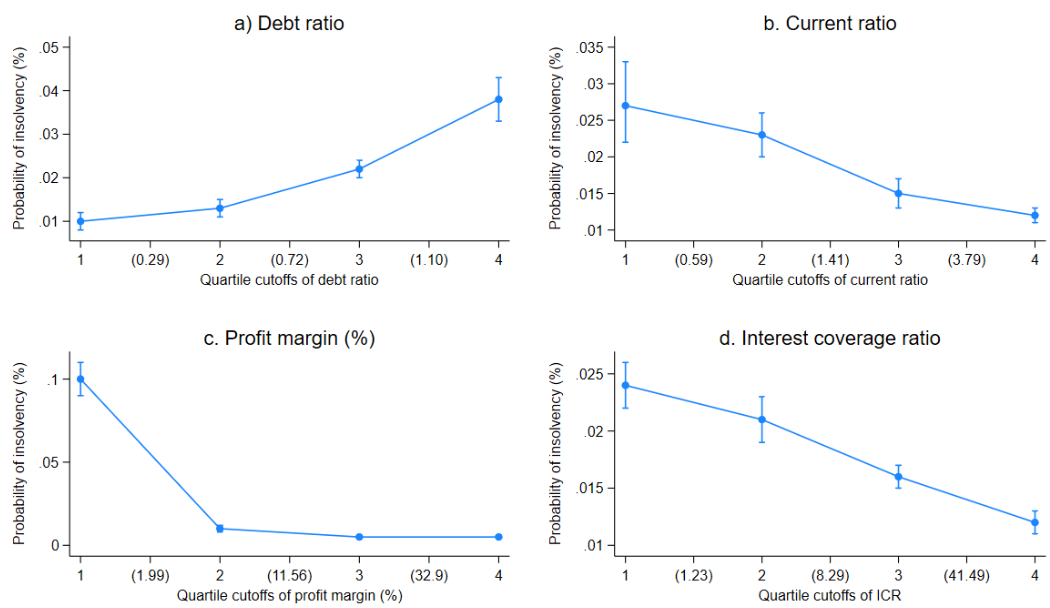
[11] We also estimate the model using a restricted sample from the post-2006 period due to discrepancies between micro and aggregate OSB insolvency numbers, as shown in Chart 1. The main conclusions of this section remain unchanged when using this sample.

[12] Quartiles are used instead of deciles because (as Chart 4 shows) most of the relevant thresholds tend to align closely with quartile cut-offs, meaning that using deciles would add little additional value while increasing computational burden significantly.

[13] For each variable, the average predicted probabilities are computed while holding all other variables at their mean values.

Consistent with the results in the previous section, we find that businesses with higher leverage, lower ICR, lower current ratio and lower profit margins are more likely to become insolvent in the following year. The probability of insolvency rises with an increasing debt ratio, with a more pronounced jump from the third to the

Chart 6: Average probability of insolvency by quartiles of financial ratios with 95% confidence intervals



Note: Error bars indicate 95% confidence intervals around the estimated values. Profit margin is defined as earnings before interest, taxes, depreciation and amortization (EBITDA)/revenue; the current ratio is near-term assets/near-term liabilities; the debt ratio is liabilities/assets and the interest coverage ratio (ICR) is EBITDA/interest expenses. The debt ratio, current ratio and ICR are expressed as ratios, while the profit margin is presented as a percentage. Our calculations are based on model predictions using Statistic Canada's dataset merging firm-level financial data from its National Accounts Longitudinal Microdata File with insolvency data from the Office of the Superintendent of Bankruptcy.

Sources: Statistics Canada and Bank of Canada calculations

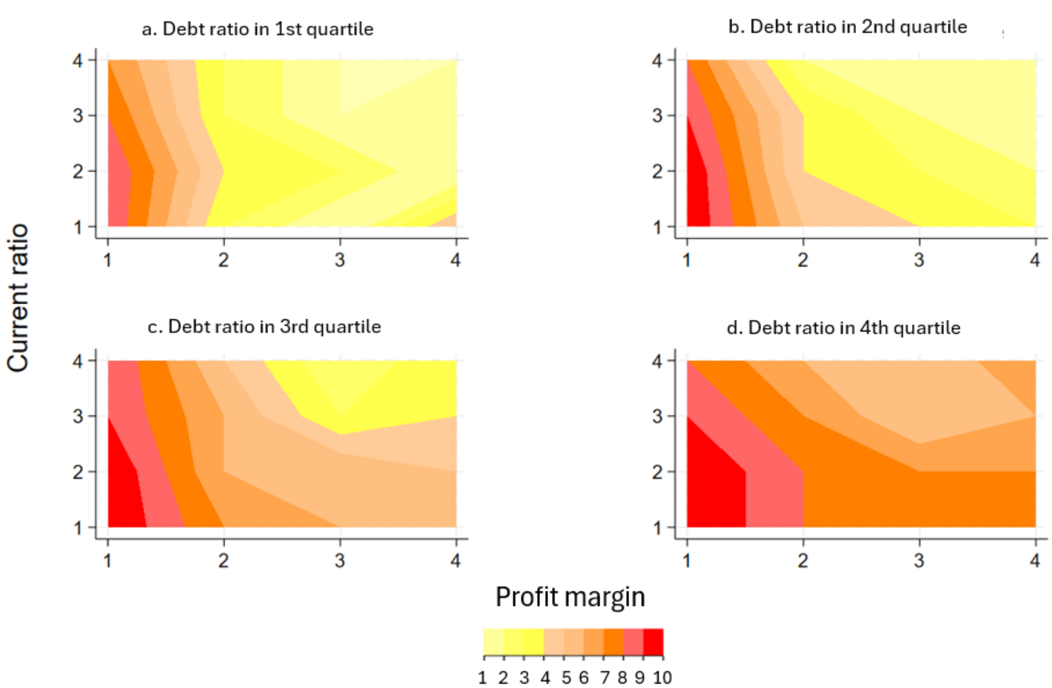
fourth quartile compared with the change from the first to the second quartile. Additionally, we find that firms with profit margins in the lowest quartile have a significantly higher probability of insolvency, while profit margins in the remaining three quartiles have minimal impact. In contrast, the probability of insolvency declines gradually and consistently across quartiles of the current ratio and ICR.

4-1. Interaction of financial ratios

Chart 7 illustrates the probability of insolvency across quartiles of the debt ratio, current ratio and profit margin. Probabilities are presented by deciles, ranked from the lowest (represented in yellow) to the highest (represented in red), with darker colours indicating higher probabilities.

The chart underscores that the interaction of financial ratios plays a more significant role in predicting insolvency than individual ratios. For instance, in the highest debt ratio quartile (shown in **Chart 7**, panel b), low liquidity significantly increases the likelihood of insolvency, specifically with low profit margin, though higher profit margin helps slightly mitigate the insolvency risk.

Chart 7: Deciles of predicted probability of insolvency by quartiles of financial ratios



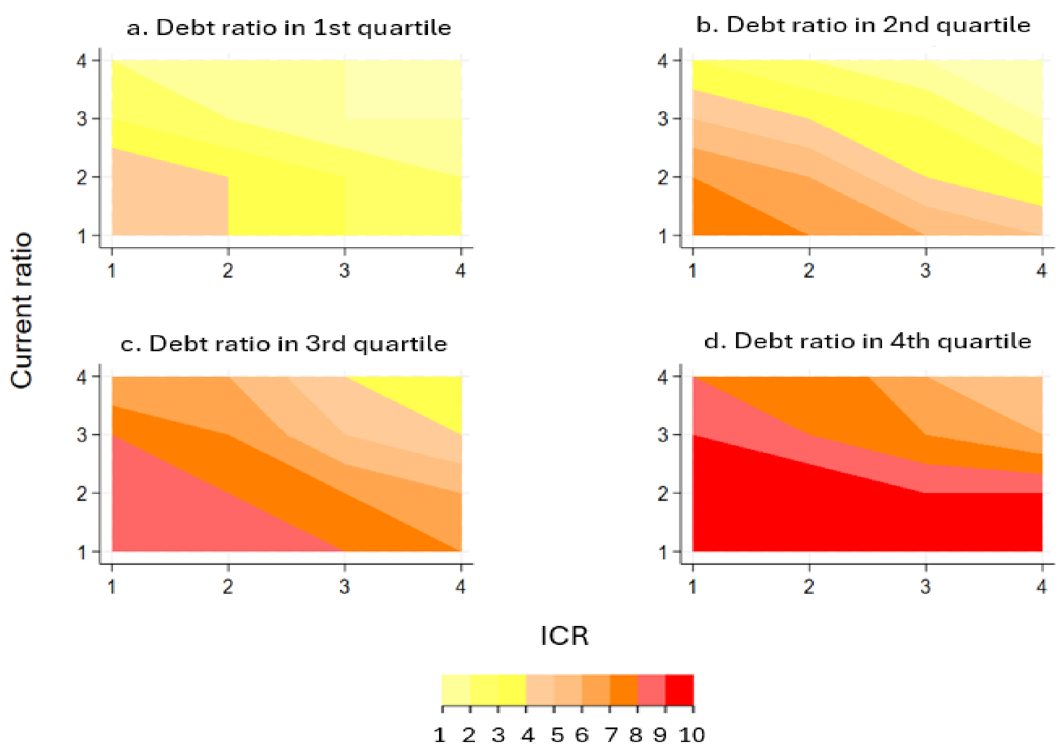
Note: Colours in the panels represent the decile of the probability of insolvency for firms meeting the criteria shown in each chart, ranging from light yellow for the first decile (i.e., lowest risk of insolvency) to dark red in the top decile. Our calculations are based on model predictions using Statistic Canada's dataset merging firm-level financial data from its National Accounts Longitudinal Microdata File with insolvency data from the Office of the Superintendent of Bankruptcy.

Sources: Statistics Canada and Bank of Canada calculations

We observe similar findings if we look at the interaction of leverage and liquidity with another financial ratio, ICR, which shows a firm's ability to service the debt. In **Chart 8** we show ICR instead of profit margin on the x-axis. In the highest debt ratio quartile (shown in **Chart 8**, panel d), low liquidity significantly increases the likelihood of insolvency, regardless of ICR, though higher ICRs help slightly mitigate the insolvency risk as long as liquidity is above the median.

Additionally, the chart reveals notable nonlinearities in the relationship between the joint distribution of these financial indicators and insolvency outcomes. For example, while the probability of insolvency shows little change when the debt ratio shifts from the first to the second quartile, the increase becomes more pronounced when moving from the third to the fourth quartile.

Chart 8: Deciles of predicted probability of insolvency by quartiles of financial ratios



Note: Colours in the panels of **Chart 8** represent the decile of the probability of insolvency for firms meeting the criteria shown in each chart, ranging from light yellow for the first decile (i.e., lowest risk of insolvency) to dark red in the top decile. Our calculations are based on model predictions using Statistic Canada's dataset merging firm-level financial data from its National Accounts Longitudinal Microdata File with insolvency data from the Office of the Superintendent of Bankruptcy.

Sources: Statistics Canada and Bank of Canada calculations

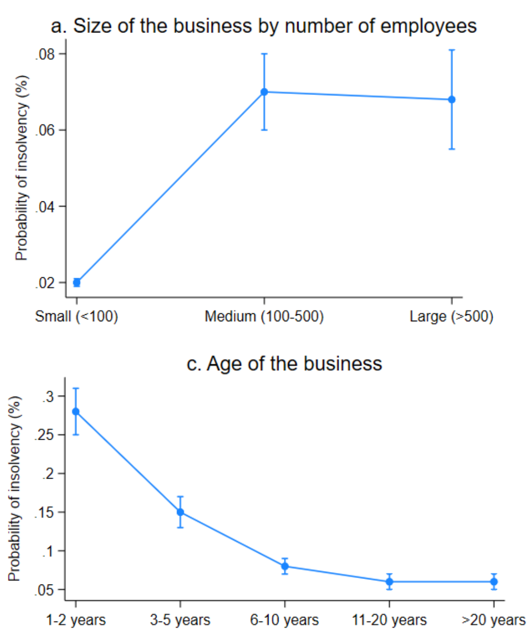
4-2. Other firm characteristics

Chart 9 illustrates the variation in the average probability of insolvency across three key firm characteristics: firm size, labour productivity and firm age.

The top-left panel presents insolvency probabilities across firm size categories. The results suggest a positive relationship between firm size and insolvency probability, with larger and medium-sized firms (more than 100 employees) exhibiting a significantly higher insolvency risk compared with small firms. In total, 99% of the firms in our sample are small (fewer than 100 employees), while 0.9% are medium-sized (100–500 employees) and 0.1% are large (more than 500 employees). Historical insolvency data indicate that large firms have a significantly higher insolvency probability, a finding that is supported by the model results.

Chart 9, panel b examines the relationship between labour productivity quartiles and insolvency probability. Labour productivity is defined as the value added per worker. Generally, firms with higher labour productivity have lower probability of insolvency.

Chart 9: Average probability of insolvency by age, size and quartiles of labour productivity



Note: Error bars indicate 95% confidence intervals around the estimated values. Our calculations are based on model predictions using Statistic Canada's dataset merging firm-level financial data from its National Accounts Longitudinal Microdata File with insolvency data from the Office of the Superintendent of Bankruptcy.
Sources: Statistics Canada and Bank of Canada calculations

The bottom panel depicts the probability of insolvency across different firm age groups. The results indicate a negative association between firm age and insolvency risk. Younger firms (one or two years old) face the highest probability of insolvency, while older firms (greater than 20 years) exhibit the lowest risk. This pattern is consistent with the notion that younger firms may be more financially vulnerable due to limited market experience, weaker financial buffers or higher failure rates associated with early-stage businesses.

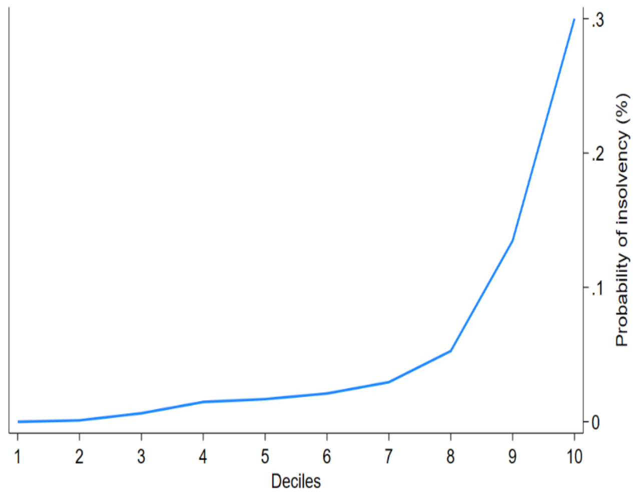
Overall, these results highlight important heterogeneities in insolvency risk across firm characteristics, emphasizing the role of productivity, firm maturity and organizational scale in shaping financial vulnerability,

4-3. Within-sample prediction

The distribution of predicted probabilities of firms' insolvency is highly skewed, as illustrated in **Chart 10**. Over 80% of the firms face an insolvency rate below 0.1% and the top decile is around 0.3%.

Table 2 shows the within-sample accuracy of the model described above. To construct the table, we sort the firms into deciles based on their fitted probability values for each year from 2000 to 2019. The table reports the proportion of insolvent or exited firms that fall into each of the five highest probability deciles in the year of their failure or exit. Additionally, it shows the percentage of insolvent or exited firms classified among the 50% of firms least likely to fail or exit.

Chart 10: Fitted probability of insolvency by decile cut points



Note: Our calculations are based on model predictions using Statistic Canada's dataset merging firm-level financial data from its National Accounts Longitudinal Microdata File with insolvency data from the Office of the Superintendent of Bankruptcy.

Sources: Statistics Canada and Bank of Canada calculations

Table 2: Percentage of insolvent/exited firms that fall into each of the probability deciles in the year of failure/exit

Decile	Insolvency (%)	Exit (%)
10	79	65
9	13	20
8	6	12
7	4	7
6	2	4
1-5	3	8

Note: Our calculations are based on model predictions using Statistic Canada's dataset merging firm-level financial data from its National Accounts Longitudinal Microdata File with insolvency data from the Office of the Superintendent of Bankruptcy.

Sources: Statistics Canada and Bank of Canada calculations

On average, 79% of the firms that file for insolvency each year are classified in the highest decile of predicted insolvency probabilities. For exit probabilities, this ratio is 65%. These results indicate that the model performs reasonably well in assigning higher insolvency probabilities to firms that ultimately become insolvent, demonstrating a relatively low Type II error rate.

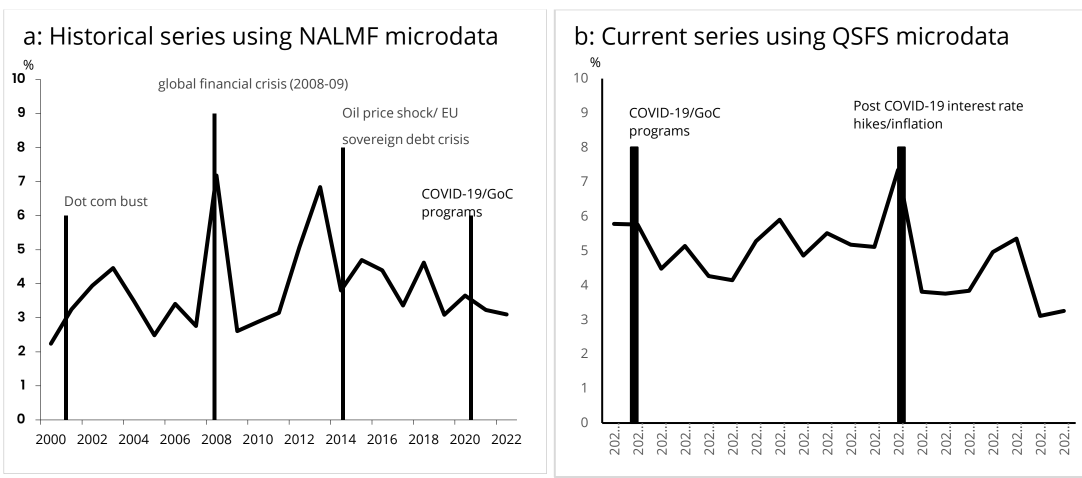
5. Applying results to corporate risk monitoring

Unfortunately, the NALMF is not suitable for real-time monitoring because the data are published annually with a two-year lag (i.e., the latest datapoint is 2023). Instead, we turn to the QSFS. Since the NALMF and QSFS data do not perfectly align, we begin by using the thresholds suggested from our empirical work in Section 3. We also use the combination of ratios suggested by the modelling work in Section 4 to bridge our results with the QSFS data.

We construct an indicator where firms are considered at risk if they pass the critical threshold in all four ratios (i.e., ICR, debt ratio, current ratio and profit margin). We then sum all the liabilities held by these at-risk firms and divide them by the total liabilities of all firms in the QSFS. The indicator can then be thought of as the share of liabilities (debt) in the sample that are held by these at-risk firms or debt at risk (**Chart 11**).[14]

Chart 11, panel a shows debt at risk constructed using the NALMF data from 2000 to 2019 and highlights that periods of increasing debt at risk are associated with periods during or just following financial stress events. **Chart 11,** panel b shows the same indicator constructed using QSFS micro-level data that are available quarterly starting in 2020 and in a timelier manner.[15]

Chart 11: Percent of liabilities held by firms beyond critical threshold in all four ratios (interest coverage, profit margin, debt-to-assets and current ratio)



Note: NALMF is Statistics Canada's National Accounts Longitudinal Microdata File, and QSFS is its Quarterly Survey of Financial Statistics. EU is the European Union, and GoC is the Government of Canada.
Sources: Statistics Canada and Bank of Canada calculations
Last Observations: 2022 (Chart 11a); 2024Q4 (Chart 11b)

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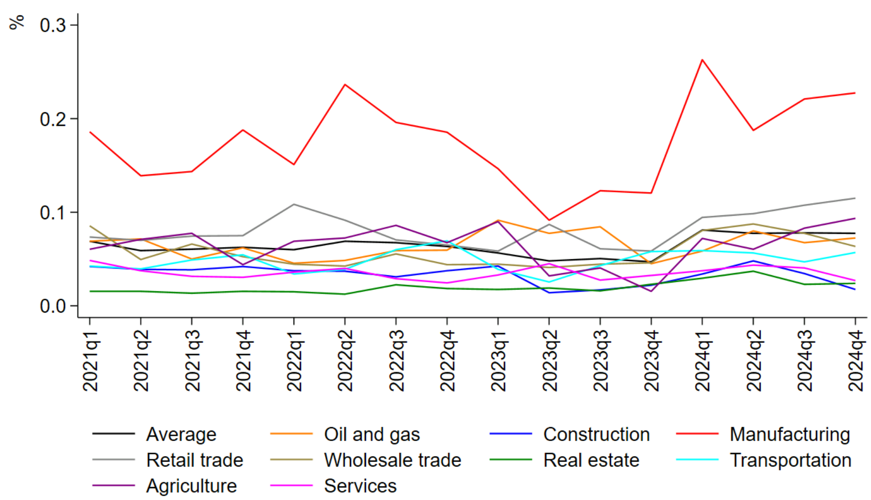
[14] For other work using the concept of debt at risk, see Banerjee and Hofmann (2018) and Feyen et al. (2017).

[15] We can see debt at risk fell as government support programs were implemented during the COVID-19 pandemic and, despite some volatility, has remained relatively subdued since. Note that the indicators in Panels A and B are not directly comparable as they come from two separate sets of data.

Next, we use our logit model to predict probabilities of insolvency using QSFS data. **Chart 12** shows the 1-year-ahead average predicted probability of insolvency across different industries from 2021 to 2024.[16] Manufacturing (red line) exhibits the highest overall probability of insolvency, while other industries, such as retail trade, wholesale trade and transportation, display relatively stable insolvency probabilities over time. Real estate (green line) consistently remains at the lower end, suggesting lower insolvency risk.

These differences across industries highlight the importance of constructing debt-at-risk measures using micro-level data, as this approach allows for the identification of specific firms or industries facing higher risk. In contrast, relying on aggregate data may obscure these sectoral heterogeneities. By applying our logit model on a quarterly basis, we aim to continuously monitor trends in debt at risk across industries to have a proactive assessment of financial vulnerabilities.

Chart 12: 1-year-ahead average predicted probability of insolvency by industry (2021–24)



Note: Our calculations are based on model predictions using Statistic Canada's dataset Quarterly Survey of Financial Statistics (QSFS).
Sources: Statistics Canada and Bank of Canada calculations
Last observation: 2024Q4

[16] The model estimation charts begin in 2021Q3 due to a break in the QSFS survey that year and the model's use of two lagged values of financial ratios.

The debt-at-risk measures presented in **Chart 11** serve as complementary indicators of insolvency risk and exhibit a strong correlation at the aggregate level. The univariate threshold approach (**Chart 11**) offers clearly defined critical thresholds that can be easily applied across different datasets, making it a practical tool for comparative analysis. Meanwhile, the multivariate econometric model (**Chart 12**) provides a more nuanced, probabilistic assessment by accounting for the interactions among financial ratios, allowing for a deeper understanding of firm-level vulnerabilities. Together, these approaches enhance the robustness of insolvency risk monitoring by balancing simplicity with analytical depth.

6. Conclusion

In summary, our results indicate that insolvent firms have noticeably worse financial ratios (i.e., higher leverage, less liquidity and lower profitability) than other firms in the same industry. We also see that key thresholds vary by industry, indicating that different industries tend to have different financial structures.

Estimating the relationship between financial ratios and the probability of different firm statuses reveals that certain financial ratios, while not significant individually, become highly significant when they interact with other financial ratios. For instance, low liquidity (current ratio) and low profitability (profit margin) do not independently lead to insolvency when leverage (debt ratio) is low. However, when leverage is high, the combination of low liquidity and profitability significantly increases the likelihood of insolvency.

We also find strong evidence of the presence of nonlinear effects in the joint distribution of financial indicators and their relationship with insolvency. For instance, moving from the third quartile to the fourth quartile of the debt ratio significantly increases the probability of insolvency. In contrast, moving from the first to the second quartile has little impact.

We use the critical thresholds found by examining insolvency rates by decile and the combination of financial ratios that are jointly significant in the logit model to build indicators of debt at risk. We then apply these debt-at-risk indicators using the timelier QSFS data for monitoring the real-time evolution of financial stability risks emanating from Canada's non-financial corporate sector. These two debt-at-risk measures complement each other: the univariate threshold approach provides clear and easily applicable risk benchmarks, while the multivariate econometric model offers a probabilistic assessment that accounts for financial ratio interactions. Combined, they enhance insolvency risk monitoring by balancing practicality with analytical depth.

These findings contribute to broader discussions on firm dynamics and productivity in Canada. For example, the negative relationship between firm age and insolvency risk highlights the financial vulnerability of younger firms, underscoring the importance of early-stage support to foster long-term viability. These results emphasize the importance of monitoring firm-level indicators to better understand the drivers of firm success, failure and growth. While this work sheds light on key aspects of financial vulnerabilities, further research is needed to more directly explore how these dynamics relate to firm productivity and broader patterns of economic dynamism in Canada.

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Appendix A: Industry group classification

Table A-1: Industry group classification

Reduced 2-digit NAICS industry group	Components
Mining, quarrying and oil and gas extraction	Mining and quarrying (except oil and gas)
	Oil and gas extraction and support activities
Construction	Construction
Manufacturing	Manufacturing
Retail	Retail
Real estate and rental and leasing	Real estate
	Automotive, machinery and equipment and other rental and leasing
Services	Professional, scientific and technical services
	Administrative and support, waste management, and remediation services
	Educational services
	Health care and social assistance
	Arts, entertainment and recreation
	Accommodation and food services
	Information and cultural industries
	Other services (except public administration)
Agriculture and wholesale trade	Agriculture, forestry, fishing and hunting
	Wholesale
Transportation, warehousing and utilities	Transportation
	Pipelines, warehousing and transportation support activities
	Utilities

Note: NAICS is the North American Industry Classification System.
Source: Bank of Canada

Appendix B: Analysis of firm exit probabilities

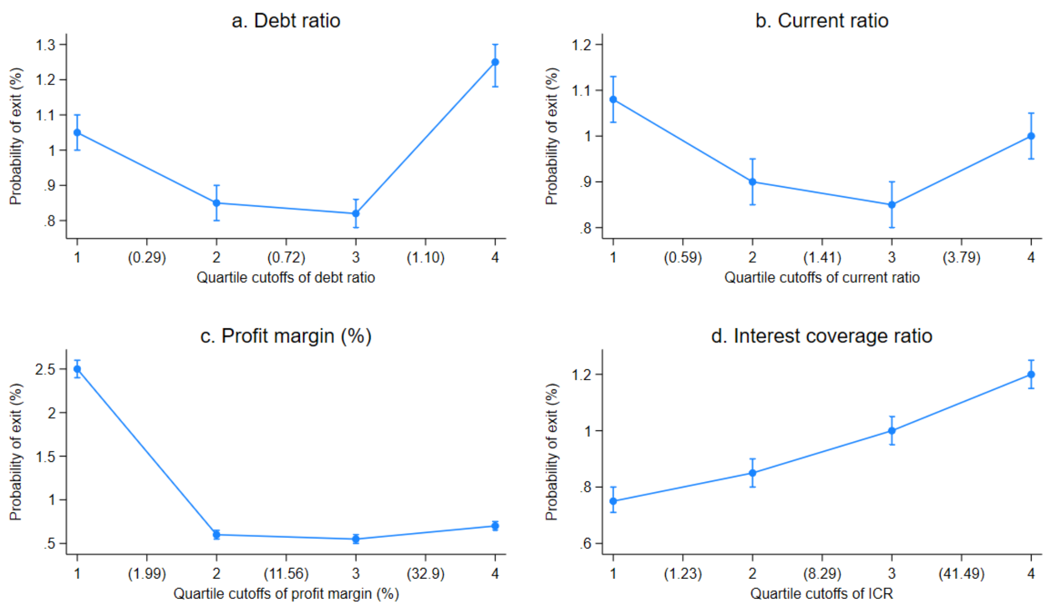
Chart B-1 presents the average probability of firm exit across quartiles of four key financial ratios: debt ratio, current ratio, profit margin and interest coverage ratio (ICR). The results highlight distinct patterns in the relationship between financial health indicators and firm exit probabilities. The probability of firm exit initially decreases across the first three quartiles of debt ratio but rises sharply in the highest quartile. This suggests that moderate levels of debt do not significantly increase exit risk, but excessive leverage significantly raises the likelihood of firm exit, likely due to increased financial distress.

The exit probability declines as the current ratio increases up to the third quartile, indicating that firms with higher liquidity are less likely to exit. However, in the highest quartile, the exit probability slightly increases, possibly reflecting inefficiencies in firms holding excessive liquid assets rather than reinvesting in productive activities.

Firms in the lowest quartile of profit margin face a significantly higher probability of exit, while firms in the upper three quartiles exhibit relatively stable and lower exit probabilities. This emphasizes the importance of profitability in reducing firm exit risk, particularly for businesses with very low profit margins.

And finally, the exit probability steadily increases as ICR increases, suggesting that firms with a stronger ability to cover interest expenses face higher exit risks. This finding reinforces the notion that not all exits are negative signals of financial stress; some may represent strategic business decisions or market-driven restructuring.

Chart B-1: Average probability of exit by quartiles of financial ratios with 95% confidence intervals



Note: Error bars indicate 95% confidence intervals around the estimated values. Profit margin is defined as earnings before interest, taxes, depreciation and amortization (EBITDA)/revenue; the current ratio is near-term assets/near-term liabilities; the debt ratio is liabilities/assets and the interest coverage ratio is EBITDA/interest expenses. The debt ratio, current ratio and interest coverage ratio are expressed as ratios, while the profit margin is presented as a percentage. Our calculations are based on model predictions using Statistic Canada's dataset merging firm-level financial data from its National Accounts Longitudinal Microdata File with insolvency data from the Office of the Superintendent of Bankruptcy.

Sources: Statistics Canada and Bank of Canada calculations

Chart B-2 presents the average exit probabilities across the firm characteristics of size, age and labour productivity. First, smaller firms (fewer than 100 employees) face the highest probability of exit, while large firms (more than 500 employees) have the lowest risk. This trend aligns with the notion that larger firms benefit from economies of scale, greater financial resources and more stable market positions, making them less vulnerable to exit.

Second, exit probability is highest for very young firms (1–2 years old), declining sharply for firms aged 3–5 years and continuing to fall for older firms. This reflects younger firms' struggle with survival due to limited market experience, financial constraints and higher operational risks. Once firms survive the early critical years, their likelihood of exit decreases substantially.

And finally, firms with lower labour productivity (bottom quartile) have the highest exit probabilities, while those in the top quartile face the lowest risk. This suggests that higher productivity provides a competitive advantage, allowing firms to generate more revenue, maintain profitability and withstand economic shocks. The smooth decline in exit probability across productivity quartiles underscores the importance of efficiency in firm survival.

Chart B-2: Average probability of exit by age, size and quartiles of labour productivity

Note: Error bars indicate 95% confidence intervals around the estimated values. Labour productivity is defined as value added per employee. Our calculations are based on model predictions using Statistic Canada's dataset merging firm-level financial data from its National Accounts Longitudinal Microdata File with insolvency data from the Office of the Superintendent of Bankruptcy.

Sources: Statistics Canada and Bank of Canada calculations

These results help explain why some financially healthy firms still face high exit probabilities. Many of these exits likely occur among smaller and younger firms, reinforcing the idea that not all exits result from financial distress—some firms may exit voluntarily due to business restructuring, acquisitions or shifts in market conditions.

Overall, firm size, age and productivity are strong predictors of exit probability, with smaller, younger and less productive firms being the most vulnerable. These findings highlight the importance of firm maturity and efficiency in ensuring long-term business survival.