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Staff analytical paper / Document analytique du personnel—2026-3

Last updated: February 26, 2026

Consumers' Path to Mortgage Delinquency

Laura Zhao
Financial Stability Department
Bank of Canada
yzhao@bank-banque-canada.ca

Jia Qi Xiao
Financial Stability Department
Bank of Canada
jxiao@bank-banque-canada.ca

Aidan Witts
Financial Stability Department
Bank of Canada
awitts@bank-banque-canada.ca

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DOI: https://doi.org/10.34989/sap-2026-3 | ISSN 3110-9195

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Acknowledgements

We would like to thank Brian Peterson, Claudia Godbout, Louis Morel and Thibaut Duprey for useful discussions and suggestions. We thank seminar participants from the Financial Stability Department, and the Economic and Financial Research Department for helpful feedback.

Abstract

This paper examines the behavioural patterns of Canadian borrowers as they progress toward mortgage delinquency. Using the full universe of TransUnion Canada borrower credit data from 2015 to 2024, we document that mortgage holders begin increasing their credit utilization roughly two years before their first mortgage delinquency. One to two years prior to becoming late on their mortgage, households frequently begin missing payments on various consumer credit products, particularly credit cards. These patterns accelerates sharply in the final six months leading up to mortgage delinquency. These empirical patterns provide a consistent and robust set of early warning signals that can be used to monitor emerging household financial stress.

Research themes: Household and business credit, Financial stability and systemic risk
JEL codes: D14, G21, G51

Résumé

Dans cette étude, nous examinons le comportement des emprunteurs canadiens à l'approche d'un défaut hypothécaire. À partir de l'ensemble des données de crédit des emprunteurs de TransUnion de 2015 à 2024, nous montrons que les détenteurs de prêts hypothécaires commencent à s'endetter davantage environ deux ans avant leur premier défaut de paiement hypothécaire. Un à deux ans avant ce défaut, il arrive souvent que les ménages commencent à manquer des paiements sur divers produits de crédit à la consommation, en particulier les cartes de crédit. Cette tendance s'accélère nettement dans les six mois qui précèdent le défaut hypothécaire. Ces observations empiriques fournissent un ensemble solide et constant de signaux d'alerte précoces qui peuvent servir à surveiller l'apparition de tensions financières chez les ménages.

Thèmes de recherche : Crédit aux ménages et aux entreprises, Stabilité financière et risque systémique
Codes JEL : D14, G21, G51

Introduction

The Canadian mortgage market plays a central role in the country's financial system and household economy. As of November 2025, outstanding residential mortgage debt in Canada reached approximately CAD 2.4 trillion, equivalent to nearly 73 % of national GDP and representing about 74 % of total household debt.[1]

As the largest liability for Canadian households, mortgages have significant implications for financial stability and represent a key channel through which monetary policy, housing demand and credit conditions interact. As a result, monitoring early signs of financial stress among mortgage borrowers is crucial for the Bank of Canada's financial stability assessment.

This paper examines the path to mortgage delinquency among Canadian households using rich micro-level data on mortgage borrowers from TransUnion Canada.[2] The dataset provides monthly snapshots of credit-active individuals and accounts nationwide. It includes detailed information on balances, credit limits, payment history and delinquencies across mortgage and non-mortgage credit products such as credit cards, auto loans and lines of credit. This enables longitudinal analysis of household credit dynamics and financial stress.

We analyze the evolution of borrower-level credit portfolio characteristics leading up to mortgage delinquency for the universe of mortgage borrowers in our sample. Our analysis reveals three key patterns in this path to mortgage delinquency:

1. About two years before becoming delinquent on their mortgage, households begin to **rely more heavily** on consumer credit, such as credit cards and lines of credit.
2. About 1 to 2 years before mortgage delinquency, delinquency rates on non-mortgage credit products **begin to increase**.
3. About six months before mortgage delinquency, both the pace of non-mortgage delinquencies and the growth in credit-utilization rates **pick up** sharply.

These patterns are robust across different time horizons and lenders, suggesting that the observed behaviours of mortgage borrowers are broadly consistent across lenders and likely to remain stable over time. Building on these identified features, we can construct borrower-level early warning indicators of future mortgage delinquency and estimate

[1] https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=3610063901

[2] To protect the privacy of Canadians, TransUnion did not provide any personal information to the Bank. The TransUnion dataset was anonymized, meaning it does not include information that identifies individual Canadians, such as names, social insurance numbers or addresses.

various aggregate delinquency probabilities—such as by geographic region, lender, age group and immigration status—to strengthen the monitoring of household financial stress.

Related literature. A well-established finding in the household finance literature is that mortgages are prioritized relative to other debts because delinquency entails significant financial and non-financial consequences. This includes the risk of foreclosure and long-term credit impairment (Guiso, Sapienza and Zingales 2013). Unsecured products such as credit cards, by contrast, carry lower immediate costs, and arrears on these products typically emerge earlier when households face financial strain.

Several studies show that non-mortgage credit behaviour is an important predictor of future mortgage distress. Elul, Souleles, Chomsisengphet, Glennon and Hunt (2010) document that credit card defaults strongly predict subsequent mortgage default, while Chatterjee, Irell and Michelson (2009) find that households often increase their use of unsecured credit prior to falling behind on their mortgage. Earlier work by Gross and Souleles (2002a, 2002b) and White (2007) highlights that households turn to credit cards to smooth consumption during income shocks, and that mounting unsecured arrears can precede distress on secured obligations.

Other research focuses on broader determinants of mortgage arrears. Dey, Djoudad and Terajima (2008) show that delinquency risk increases sharply when household debt-service ratios exceed key thresholds. Studies such as Fuinhas, Marques, and Adams (2022) and Krainer and Laderman (2011) examine life-cycle dynamics and regional variation, while Ganong and Noel (2020) decompose the mechanisms leading to default using a structural hazard framework. Bank of Canada research has also identified emerging vulnerabilities; for example, Allen, Carmichael, Clark, Li, and Vincent (2024) show that reliance on parental financial support among first-time homebuyers is associated with higher subsequent delinquency risk.

While this literature provides important insights into vulnerability and default, few studies have systematically mapped the high-frequency *temporal progression* of behaviours leading up to mortgage delinquency, particularly using large-scale Canadian microdata. Our paper fills this gap by leveraging the granularity of the full TransUnion Canada universe to trace the evolution of borrower credit behaviour, providing new evidence on the timing and magnitude of behavioural changes preceding mortgage arrears.

Key patterns preceding mortgage delinquency

Data description

Our empirical analysis draws on the full TransUnion consumer credit bureau dataset covering the period from 2015 to 2024. The dataset includes more than 9 million mortgage holders and over 100 mortgage lenders, representing roughly 80% of all household mortgages in Canada. Mortgage borrowers typically hold multiple forms of credit: approximately 90% also have at least one credit card and more than one-third hold auto loans or unsecured lines of credit. This broad coverage allows us to study household credit behaviour within a comprehensive view of borrowers' total debt portfolios.

A key strength of the TransUnion dataset is its monthly panel structure, which enables us to follow the same borrowers over extended periods and observe how their credit portfolios evolve as economic or financial conditions change. This longitudinal tracking is critical for identifying behavioural patterns that emerge well before borrowers fall behind on their mortgage payments.

At the account level, the dataset provides rich detail for each major credit product, including mortgages, credit cards, auto loans, installment loans, home-equity lines of credit (HELOCs) and unsecured lines of credit. For every account, TransUnion reports detailed information, including outstanding balance, credit limit, required minimum payment, payment status, delinquency history and account opening dates. In addition to product-specific information, the dataset includes several borrower characteristics—most notably age and geographic location—which enable us to examine differences in credit behaviour across demographic and regional groups.

Taken together, the combination of granular account-level information and a complete monthly borrower panel make the TransUnion microdata well suited for detecting early warning signals of mortgage distress.

Methodology

Constructing a consumer panel

To document the path toward mortgage delinquency, we first construct a consumer-level panel by aggregating account-level information from TransUnion. This step is essential because borrowers typically hold multiple credit products, such as mortgages, credit cards, auto loans and lines of credit, and the dynamics across these products jointly shape a household's financial position. By linking all accounts belonging to the same individual, the consumer panel provides a consolidated view of each borrower's full credit portfolio.

This consumer-level structure offers several advantages. It allows us to track how borrowers change credit usage across different products as financial stress builds, measure total debt and overall delinquency exposure and observe interactions between secured and unsecured borrowing. Crucially, it enables us to trace the sequence and timing of behavioural changes for each consumer, such as rising utilization and emerging arrears, leading up to mortgage delinquency.

Let i represent an individual consumer and $j \in \{1, \ldots, J\}$ represent a specific product type (e.g., $j = 1$ for mortgages, $j = 2$ for credit cards). For each product type j, consumer i may hold multiple accounts. Let $A_{i,j}$ denote the set of all accounts of type j belonging to consumer i.

For each account $a \in A_{i,j}$, define the account-level state vector:

$$\vec{X}_{i,j,t}^{(a)} = [x_{i.j,t}^{(1,a)}, x_{i.j,t}^{(2,a)}, \ \ldots \ ],$$

where each component $x_{i.j,t}^{(1,a)}$ represents a specific attribute of account a at time t (e.g. balance, credit limit, utilization rate, delinquency status).

We then define the aggregated state vector for consumer i and product type j at time t as:

$$\vec{X}_{i,j,t} = f\left(\vec{X}_{i,j,t}^{(a)} \mid a \in A_{i,j}\right),$$

where $f(\cdot)$ is an aggregation operator appropriate for each variable (e.g., sum of balances, maximum delinquency status, average utilization).

The complete credit profile of consumer i at time t is then represented as a vector:

$$\vec{P}_{i,t} = [\vec{X}_{i,1,t}, \vec{X}_{i,2,t}, \ldots, \vec{X}_{i,J,t}].$$

Identifying the first mortgage delinquency

Let $X_{i,m,t}$ represent the state of the mortgage product m for consumer i at time t. We define a binary indicator $D_{i,t}$ that flags whether the consumer is at least 30 days in arrears on its mortgage:[3]

$$D_{i,t} = \begin{cases} 1, & \text{if the mortgage is } \geq 30 \text{ days delinquent,} \\ 0, & \text{otherwise.} \end{cases}$$

We then define the event time T_i as the first month in which consumer i records a delinquency, provided they had a clean record for the preceding 24 months:

$$T_i = \min\{\, t \mid D_{i,t} = 1 \text{ and } \sum_{s=t-24}^{t-1} D_{i,s} = 0\}.$$

[3] The subsequent results are robust to alternative definitions of the delinquency, including 60-day and 90-day arrears thresholds.

This constraint ensures that T_i represents a significant transition rather than a recurring or incidental missed payment. [4]

Portfolio dynamics leading to first mortgage delinquency

To characterize the path toward delinquency, we examine the evolution of the consumer's credit vector $\vec{P}_{i,t}$ as t approaches T_i. We define the observation window as $\tau \in \{-W, \dots, -1\}$, where W is the number of months prior to the first mortgage delinquency month. The credit profile at event time τ is:

$$\vec{P}_{i,\tau} = [\vec{X}_{i,1,\tau}, \vec{X}_{i,2,\tau}, \dots, \vec{X}_{i,J,\tau}].$$

To analyze borrower behaviour in the observation window, we group borrowers into cohorts based on T_i. For each calendar month t, we define

- Delinquent Cohorts ($\mathcal{C}_{\mathcal{D},t}$) : $\mathcal{C}_{\mathcal{D},t} = \{i \mid T_i = t\}$
- Control Cohorts ($\mathcal{C}_{\mathcal{C},t}$): a random sample from the borrowers whose mortgages are not delinquent at t, i.e. $\mathcal{C}_{\mathcal{C},t} \subset \{i \mid D_{i,s} = 0, \forall s \in [t-24, t]\}$.

Our sample includes $N = 110$ cohorts in each group.

To isolate the effect of "distance from delinquency," we compute the mean of $\vec{X}_{i,j,\tau}$ for each cohort and then average across all cohorts. For a specific variable $x_{i,\tau}$ (e.g., credit card utilization), the mean behaviour is:

$$\bar{x}_\tau^{\text{Delinquent}} = \frac{1}{N}\sum_{t=1}^{N}\left(\frac{1}{|\mathcal{C}_{\mathcal{D},t}|}\sum_{i\in C_{D,t}} x_{i,\tau}\right)$$

$$\bar{x}_\tau^{\text{Control}} = \frac{1}{N}\sum_{t=1}^{N}\left(\frac{1}{|\mathcal{C}_{\mathcal{C},t}|}\sum_{i\in C_{D,t}} x_{i,\tau}\right).$$

We consider a range of variable $x_{i,\tau}$ such as the utilization rate and non-mortgage product delinquency status. In the results section that follows, we present the salient patterns we observed from the data.

Results

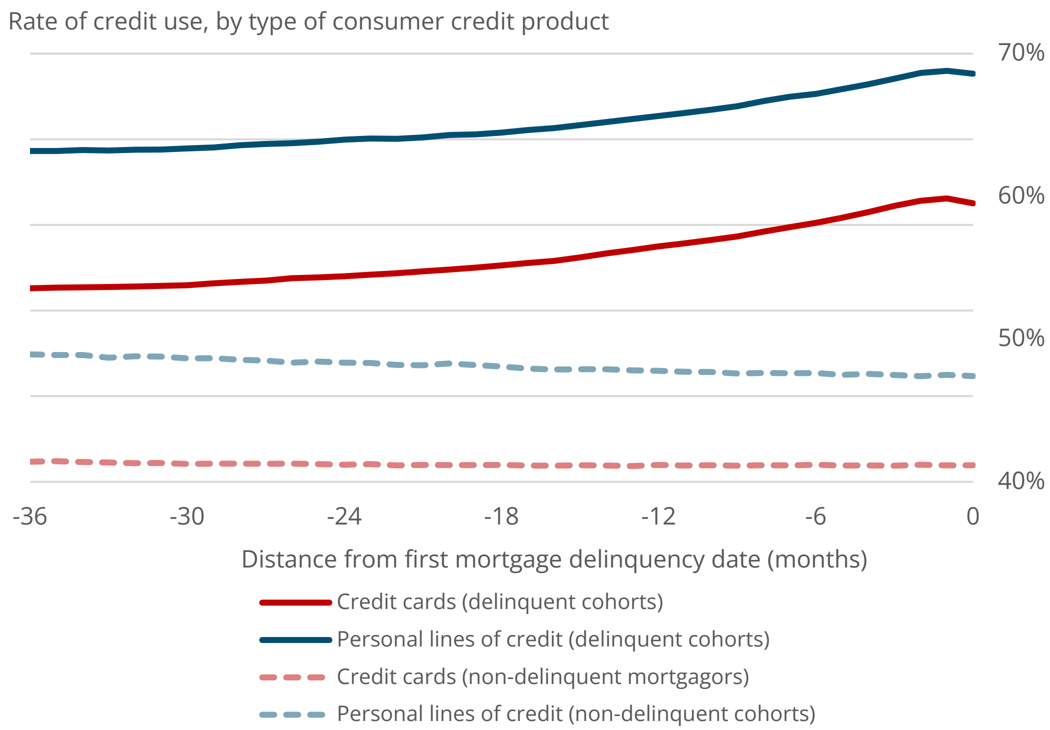
Chart 1 reveals that credit utilization on revolving products, such as credit cards and lines of credit, begins rising steadily for future delinquent borrowers roughly two years before their first mortgage delinquency event. In contrast, utilization among non-delinquent (control) cohorts remains stable over the same period. Moreover, we find that there is a

[4] The 24-month "clean" period is needed to capture a true state change with the goal of avoiding excessive sample attrition; it also reflects the timeframe over which consumer credit behaviour typically recovers from a previous credit event.

noticeable difference in credit utilization levels between households that will default and those that remain current on their mortgage payments.

Between 1 and 2 years before the first mortgage delinquency event, non-mortgage products delinquency rates rise. As shown in **Chart 2**, the credit card delinquency rate starts to increase the earliest, followed by other credit products such as auto loans, HELOC, lines of credits and installment loans.[5]

Chart 1: *Credit utilization rate starts to increase more than 24 months before mortgage delinquency*



[5] We also compute the same delinquency rates for the control cohorts. As expected, delinquency rates for these cohorts are close to zero and align with the historical average delinquency observed for the TransUnion sample.

***Chart 2**: Non-mortgage products delinquencies lead mortgage delinquencies*

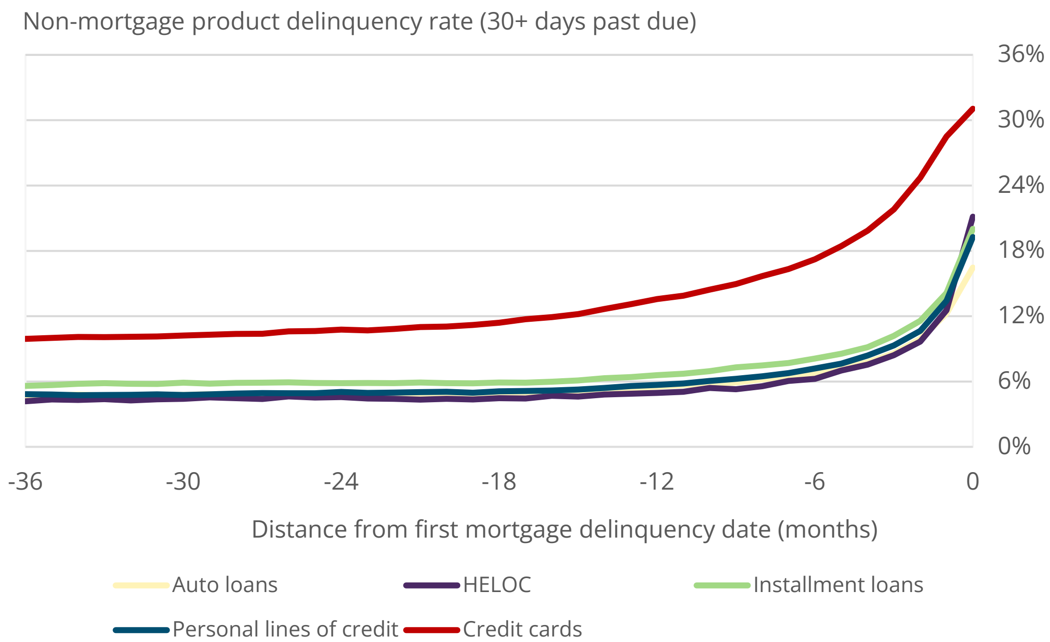
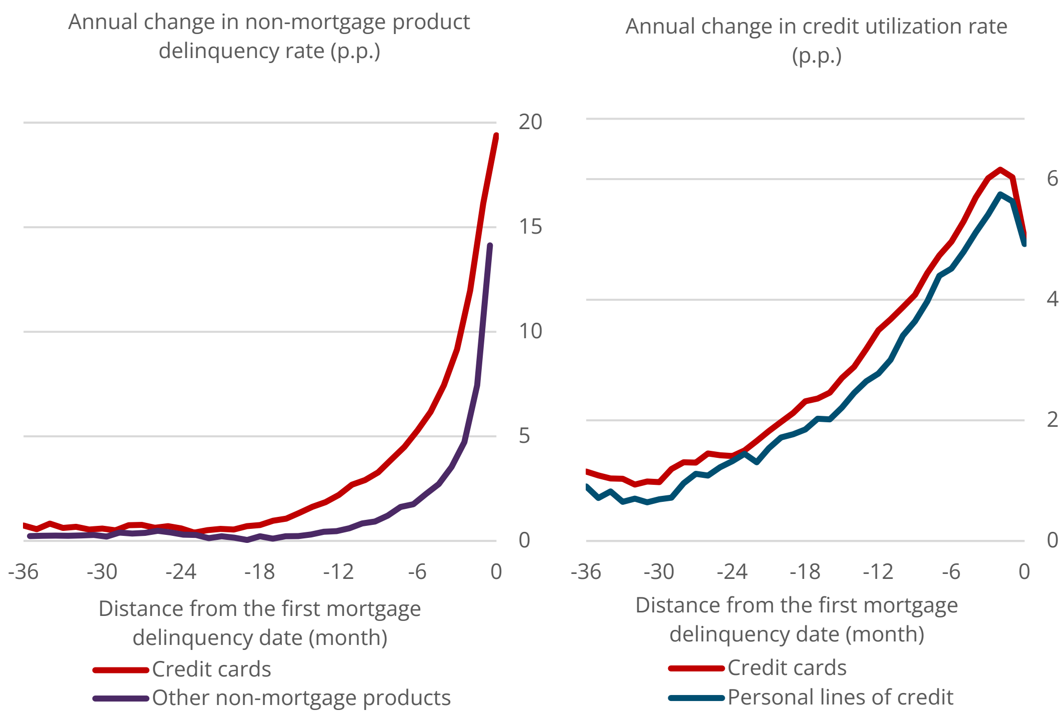


***Chart 3**: Increases in non-mortgage product delinquency rates and credit utilization rates pick up as mortgage delinquency approaches[6]*



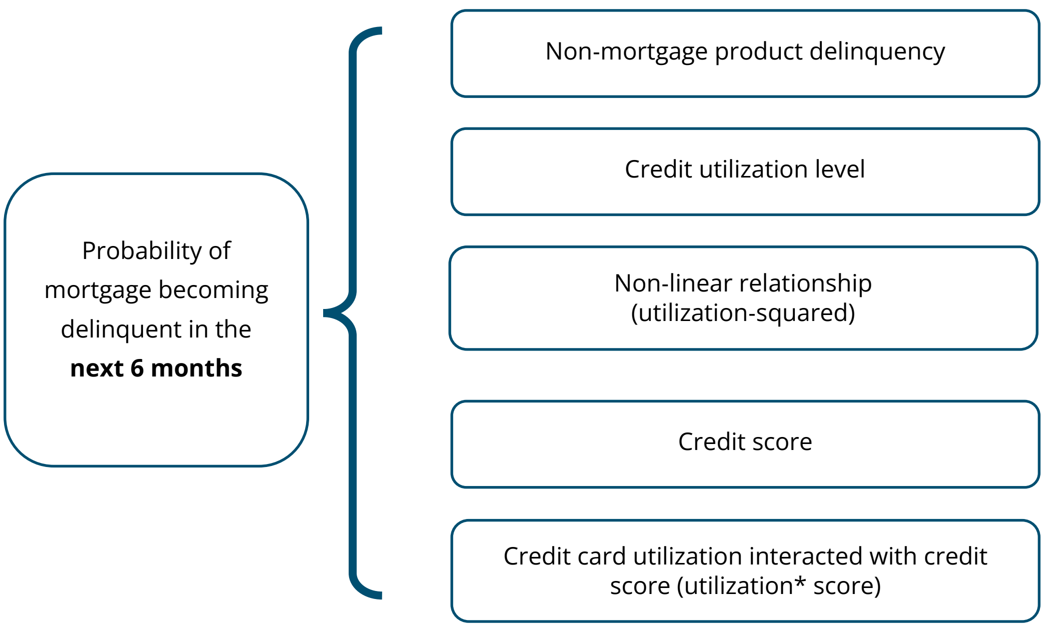
[6] Annual change in delinquency rate for non-mortgage product is the average of the annual changes of auto loans, HELOC, Installment loans and personal lines of credit.

The upward trend in both non-mortgage delinquency and credit utilization rates intensifies as mortgage delinquency approaches. **Chart 3** plots the year-over-year changes in these rates, capturing acceleration of financial stress. For delinquent cohorts, the credit card delinquency rate increases by as much as 20 percentage points, and the credit utilization rate rises by 6 percentage points on average as the mortgage delinquency event nears.

We further analyze the robustness of the path-to-delinquency pattern by running fixed-effects estimates on the "distance from mortgage delinquency" variable. The pattern is robust across time and lenders. Details of the analysis can be found in the appendix.

Empirical framework to estimate the probability of future delinquency

With these behavioural features identified, we estimate the probability of future mortgage delinquency based on the observed patterns from borrowers' credit portfolios, including some additional controls. The diagram below shows the structure of our estimation strategy.



The estimation equation is given by:

$$P_{i,t+1\rightarrow t+6} = \alpha \cdot Arrear_{i,t} + \beta \cdot Util_{i,t} + \gamma \cdot CS_{i,t} + \rho \cdot CS_{i,t} \times Util_{i,t} + \mu \cdot Util_{i,t}^{2} + Const + \varepsilon_{i,t}.$$

Here $P_{i,t+1\rightarrow t+6}$ denotes the probability that borrower $i$becomes mortgage-delinquent at any point over the subsequent six months. The variable $Arrear_{i,t}$ is a dummy variable indicating credit card delinquency, which serves as a proxy for broader non-mortgage financial stress. To capture the non-linear relationship between credit utilization and delinquency risk, we include both the credit card utilization rate ($Util_{i,t}$) and its quadratic term ($Util_{i,t}^2$). We also include an interaction term between utilization and credit score to account for the differential impact of debt accumulation across the credit spectrum. This allows the model to capture the fact that a marginal increase in utilization typically signals greater financial distress for low-score borrowers than for their high-score counterparts. Finally, we control for the borrower's credit score ($CS_{i,t}$) to account for baseline creditworthiness.

Table 1: *Estimation of probability of mortgage delinquency over the next 6 months* ($P_{i,t+1\rightarrow t+6}$)

Explanatory variable	Marginal effect (OLS)	Marginal effect (Probit)	Contribution to total variation (Shapley value, OLS)[7]
Utilization × credit score[8]	0.025***	0.000092	34.5%
Credit score (/100)	–0.0074***	-0.0093***	29.1%
Credit card arrears dummy	0.037***	0.0030***	18.5%
Utilization	–0.054***	-0.017***	9.9%
Utilization-squared	0.019***	0.022***	9.7%

Table 1 presents the results of our empirical model, estimated over the period from January 2015 to December 2019. To mange the computation intensity of the full TransUnion universe, the model is estimated using a 5% random sample.

The results confirm that behavioural variables have substantial predictive power for future mortgage delinquency. Credit card arrears and the squared utilization term are both positive and statistically significant, with the latter indicating that delinquency risk rises non-linearly as borrowers approach their credit limits. The interaction between utilization and credit score accounts for the largest share of the model's explanatory power (34.5%). By inverting the credit score in this interaction term, we capture heterogeneity in the risk associated with revolving debt: a given increase in utilization signals significantly greater financial stress for lower-score borrowers. While the average marginal effect of the interaction term lacks statistical significance in the Probit model, this is primarily driven by the high proportion of stable, low-risk households in the TransUnion universe. In a non-linear Probit framework, the marginal effect of an interaction is conditional on the baseline risk; as most borrowers are far from the default threshold, their individual marginal effects are mathematically compressed toward zero.

The Shapley value decomposition illustrates that while the baseline credit score is important (29.1%), the collective behaviour features – including utilization patterns and

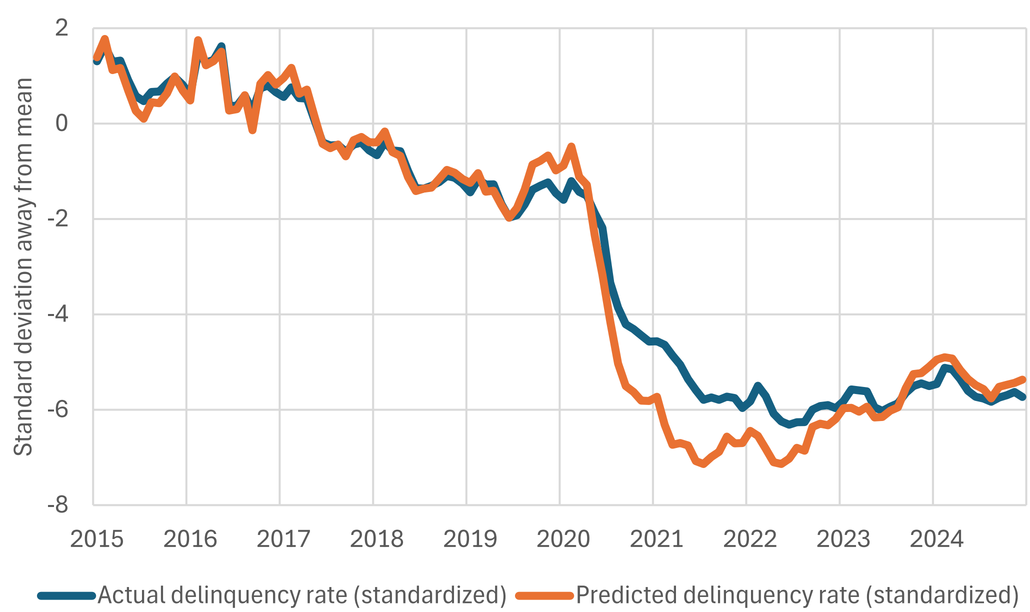
[7] Shapley value decomposition on the pseudo r-squared gives similar results.

[8] We define the interaction as utilization * (900 – Credit Score)/100. The credit score is inverted so that the interaction coefficient reflects the compounded effect of high utilization and lower creditworthiness.

arrears – account for over 70% of total variation. This highlights the value of dynamic behavioural information in predicting mortgage stress beyond standard credit metrics and underscores its usefulness for early-warning financial stability surveillance.

We also examine the model's out-of-sample performance by generating borrower-level predictions from January 2020 to December 2024 and aggregating these predictions to the national level. In **Chart 4**, the portion of the predicted series prior to 2020 reflects the model's in-sample fit, while the segment from 2020 onward represents out-of-sample predictions. The model maintains a high degree of predictive accuracy beyond the estimation window, closely tracking realized mortgage delinquency through substantial macroeconomic and financial disruptions. This strong out-of-sample performance suggests that the underlying behavioural relationships—most notably the lead–lag dynamics between revolving credit distress and subsequent mortgage arrears—are structurally stable over time.

Chart 4*: Estimated probability of mortgage delinquency shows strong out-of-sample performance*



Robustness check using TU-RESL matched data

While TransUnion provides comprehensive data on credit portfolios, it lacks specific mortgage-level attributes such as Loan-to-Value (LTV) and the Mortgage Debt Service Ratio (MDSR). To address these data gaps and test the robustness of our findings, we integrated the TransUnion bureau data with the OSFI regulatory loan-level mortgage origination dataset (RESL). This merge followed the probabilistic matching methodology established by Khan and Xu (2022).[9] By appending these underwriting variables to our consumer panel, we were able to re-estimate our baseline models using these characteristics as additional control variables.

The estimation results for the six-month-ahead mortgage delinquency forecast, incorporating additional controls from the TransUnion-RESL matched data, are presented in **Table 2**. As expected, a higher MDSR at origination is positively and significantly associated with subsequent delinquency risk. LTV at origination, by contrast, is not statistically significant. This likely reflects two factors: first, the analysis does not distinguish between insured and uninsured mortgages; and second, subsequent house price movements weaken the relevance of origination-time LTV as a measure of current borrower equity relative to updated valuations.

Table 2: *Estimation of probability of mortgage delinquency over the next 6 months ($P_{i,t+1\rightarrow t+6}$) with additional controls from TransUnion-RESL matched data*

Explanatory variable	Marginal effect	Contribution to total variation (Shapley value)
Utilization × credit score	0.025***	38.7%
Credit score (/100)	–0.0011***	21.7%
Credit card arrears dummy	0.027***	16.9%
Utilization	-0.038***	10.0%
Utilization-squared	0.0041**	10.0%
Mortgage payment growth (6m)	0.00027***	2.1%
Credit card spending dummy[10]	0.0067***	
Credit limit growth	–0.0000	
HELOC dummy	–0.0000	
MDSR	0.0024***	0.7%
LTV at origination	0.0005	

To evaluate the relative predictive power of these features, we also perform a Shapley value decomposition. Despite the inclusion of several mortgage characteristics, credit utilization and credit card arrears remain the primary drivers of delinquency, collectively explaining more than 70% the total variation. This finding aligns with Elul, Souleles,

[9] A limitation of this matched data is that successful matches are restricted to a specific set of lenders, hence this sample represents a subset of the comprehensive TransUnion data used to document earlier patterns.

[10] Dummy equals 1 if the drop in credit card spending over past 6 months is larger than 70 %.

Chomsisengphet, Glennon, and Hunt (2010), reinforcing the role of unsecured credit behaviour as a critical leading indicator for mortgage distress.

Factors such as HELOC availability and credit limit growth do not yield statistically significant implications for future delinquency in this model.

While mortgage payment growth and consumer spending (proxied by credit card activity) are statistically significant, their contributions to the total variation are relatively small. This likely reflects an endogenous relationship wherein behavioral variables, such as revolving credit utilization, respond to fluctuations in debt obligations and spending shocks well before a formal delinquency occurs.

Ultimately, these coefficients should not be interpreted as the total causal effect of each variable, but rather as a predictive framework. This model provides a robust tool for monitoring the most influential observables to identify emerging stress among mortgage holders at the most granular (borrower) level.

Conclusion

This paper documents a clear and measurable behavioural progression toward mortgage delinquency among Canadian households. Using the full universe of TransUnion credit bureau data, we show that rising credit utilization and the emergence of arrears on non-mortgage products consistently precede missed mortgage payments, often by a substantial margin. These patterns highlight unsecured credit behaviour as a key early manifestation of household financial stress.

The identified behavioural signals are robust across time and lender types, spanning D-SIBs and alternative lenders alike. Our empirical framework demonstrates that a relatively small set of dynamic variables—namely unsecured credit arrears, credit card utilization, and their interaction with borrower creditworthiness—accounts for the majority of the model's predictive power. The strong and sustained out-of-sample performance of the model, including through periods of significant economic disruption, further suggests that these behavioural relationships are structurally stable. Together, these results underscore the value of incorporating high-frequency behavioural dynamics into frameworks for monitoring household financial vulnerability.

While the analysis focuses on credit-portfolio dynamics, future work could further enhance predictive accuracy by incorporating additional sources of risk, such as micro-level income or employment shocks, as well as broader macroeconomic conditions. In addition, although this study captures key non-linearities through interaction and quadratic terms, more flexible machine-learning approaches may be well suited to uncovering higher-order relationships in the data.

Overall, these findings provide a coherent and empirically grounded set of early-warning indicators for financial stability surveillance. By identifying emerging vulnerabilities well before they materialize as mortgage defaults, the proposed framework supports a more proactive and forward-looking approach to monitoring financial stress among Canadian households.

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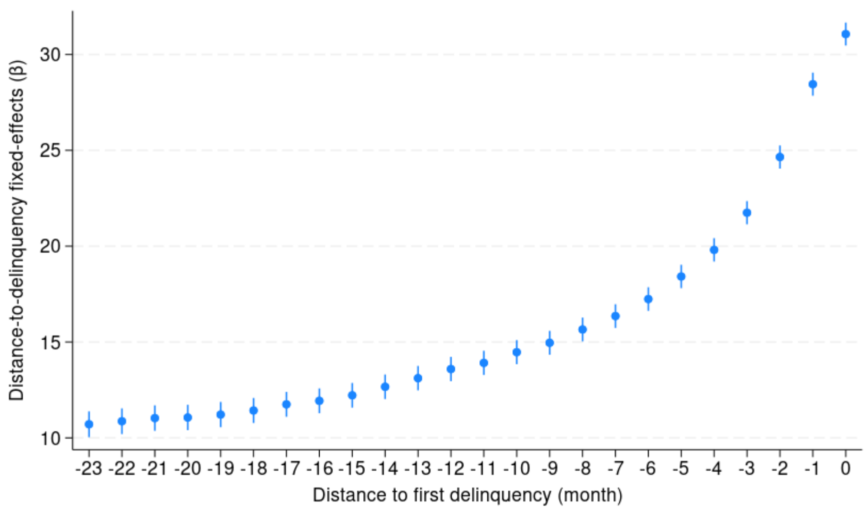
Appendix

We estimate the distance-to-delinquency effects using the specification: $\pi_{i,a,t} = \boldsymbol{\beta_a} + \varepsilon_{i,a,t}$, where $\pi_{i,a,t}$ is the 30+ days past due rate of cohort i at time t and with "distance to first delinquency (month)" a. We plot the distance-to-delinquency fixed-effects with 95% confidence interval:

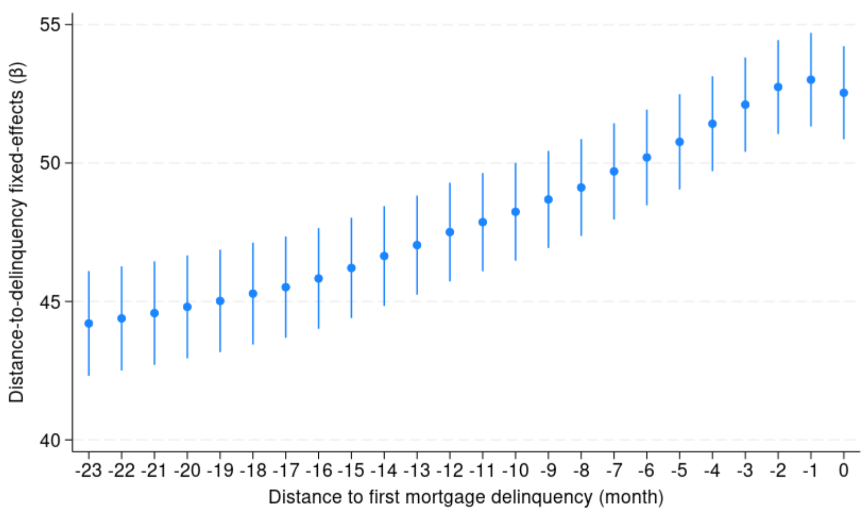
Chart A1: *Distance-to-delinquency fixed effects for non-mortgage delinquencies (credit card)*



As shown in the chart, the path-to-delinquency pattern is statistically significant with tight confidence bands. Moreover, the result is robust to controlling for cohort and time fixed effects, i.e. $\pi_{i,a,t} = \alpha_i + \beta_a + \gamma_t + \varepsilon_{i,a,t}$.

We also run the same analysis for credit utilization rates. The path pattern is still very significant despite wider confidence bands.

Chart A2: *Distance-to-delinquency fixed effects for credit card utilization*



The path toward mortgage delinquency is robust across lender subsamples, as shown in the **Chart A3**:

Chart A3: *Consistent patterns for different lender groups*