Banking transaction behaviour

Helping lenders make more confident decisions for thin file applicants

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An Experian whitepaper

Executive summary

Seeing more of the credit story

Credit decisioning works best when lenders have a clear, reliable view of risk. In Australia, Comprehensive Credit Reporting (CCR) has strengthened that view by making positive credit behaviour more visible, but coverage remains uneven and some applicants leave relatively few signals in their credit files.

This paper examines what that means for lenders when assessing thin file applicants, and what can be learned when credit bureau information is augmented with banking transaction behaviour to improve decision confidence while maintaining disciplined risk management.

About the case study

We conducted a case study designed to examine whether thin file consumers are disadvantaged in credit decisioning, and whether alternative data sources, particularly banking transaction data, can help lenders make more informed and inclusive decisions while maintaining or reducing risk.

The case study showed combining bureau and transaction signals delivered the strongest observed result – a **43% reduction in bad rates** versus credit bureau data alone at the same approval rate.

What you will learn

- **Section 1:** The size of the thin file segment in Australian credit applications
- **Section 2:** Evidence of approval disadvantage where visibility is limited
- **Section 3:** Case study – comparison of scoring approaches and observed outcomes at 12 months
- **Section 4:** Behavioural drivers – why transaction data remains informative when credit files are thin
- **Section 5:** Implications for strategy and policy design

What you can take away

This paper includes questions intended to help lenders audit current thin-file decisioning approaches against growth goals, risk thresholds and operational constraints.

Here's one question to get you started:

> When credit history is limited, where does uncertainty most influence outcomes in your funnel – the cut-off, pricing outcomes, or the path to manual review?

Setting the context

What changes when visibility is uneven

Why explore banking transaction behaviour

Banking transaction data offers a complementary source of insight into consumer financial behaviour, capturing frequently updated activity – income regularity, spending patterns, bill payments and cashflow management – that may not be visible in credit bureau files. In credit decisioning, these behavioural signals can help lenders better understand a consumer's financial capacity and stability, particularly where traditional credit history is limited or absent.

What international evidence suggests

International studies indicate that Positive Credit Reporting regimes can reduce data asymmetry by improving visibility into repayment behaviour across a wider range of products and sectors, including non-traditional credit and pseudo-credit industries such as telecommunications and utilities. They also suggest that consumers with positive repayment histories in these sectors often demonstrate credit behaviour equal to or better than mainstream borrowers, and that even consumers with no formal credit history may present low risk where income is consistent and bill payment behaviour is reliable.

The Australian experience

Australia's adoption of Comprehensive Credit Reporting (CCR) has improved fairness by making positive credit behaviour more visible, but its impact remains uneven and depends on participation and coverage. Where relevant lenders do not participate, repayment histories can remain invisible to prime lenders, and consumers who manage finances well without using conventional credit products may still leave few usable signals in traditional reporting, meaning lending decisions may be made on incomplete information.

Case study context

Study population and timeframe	The analysis was based on a near-prime lender's credit applicants over a 12-month period, with credit performance measured 12 months after account opening by comparing thin file applicants to credit-experienced peers.
Cohort definition (thin file)	For this study, thin file consumers were defined as having little or no recent credit history (most with no visible credit history, while a minority had no current credit holdings and, at most, one account closed within the past two years), no known derogatory credit history, having applied for credit with a near-prime lender, and having been granted credit by that lender.
Data and measurement	Predictive accuracy was evaluated using application data (assessed via the lender's internal application score), credit bureau data (including credit enquiries and limited account history), and banking transaction data (including income regularity, bill payments, spending patterns and payment methods), tested individually and in combination, with credit risk assessed using observed bad rates at 12 months.

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How large is the thin file population?

The first aspect of our investigation focused on determining the size of the thin file population relative to the entire credit-active population (i.e. credit-active includes all consumers actively seeking credit). By answering this question, we were able to assess whether addressing data asymmetry could deliver a significant benefit to consumers and lenders, as well as to the broader economy.

Analysis of credit bureau data for credit card and personal loan applicants over a 12-month period showed that a substantial proportion had minimal or no visible credit history.

Table 1: Percentage of *credit card* applicants with no accounts open in the last 24 months

% of Applicant Population (Timeline: 12-months period)	No accounts open in previous 24m Thin file (% Applicants)
'Big 4' banks	16%
Regional banks	10%
International banks and prime non-bank lenders	27%
Peer-to-peer / near-prime / sub-prime lenders	18%

Table 2: Percentage of *personal loan* applicants with no accounts open in the last 24 months

% of Applicant Population (Timeline: 12-months period)	No accounts open in previous 24m Thin file (% Applicants)
'Big 4' banks	18%
Regional banks	18%
International banks and prime non-bank lenders	9%
Peer-to-peer / near-prime / sub-prime lenders	24%

What the data reveals

The last result is particularly important: it suggests near-prime and sub-prime lenders may take on a large proportion of consumers with no existing credit and little, if any, historical credit footprint.

Rather than only sourcing customers with impaired credit, these higher-cost lenders also serve a sizeable population of thin file consumers.

This study aimed to demonstrate whether a sizeable cohort was suitable for prime lenders – those who may be unfairly excluded today.

Questions to consider

How does the prevalence of thin file applicants vary across your products and acquisition channels?

Where do you currently apply additional friction (manual review, documentation, conservative pricing) to manage uncertainty in thin-file decisions?

2 Are thin file applicants disadvantaged?

Having established that the thin file population is sizeable, the next step was to assess whether these consumers face a disadvantage when seeking credit. Specifically, we examined whether applicants with limited credit history were less likely to be approved than their credit-experienced counterparts – and whether this exclusion is justified when assessing their risk. Applicants were segmented into three groups:

Thin file group 1

No credit holdings in the past two years

Thin file group 2

No current credit holdings and only one account closed in the past two years

Credit-experienced

At least one active credit account or more than one account closed in the past two years

Using credit bureau data, we inferred whether an applicant was approved by identifying whether a credit account was opened following an enquiry.

Table 3: Relative approval rate of thin file credit card applicants compared to credit-experienced applicants

Difference in accept rate	Thin file group 1	Thin file group 2
'Big 4' banks	-33%	-13%
International banks and prime non-bank lenders	-54%	-24%
Regional banks	-55%	-39%
Near-prime lenders	-69%	-56%

Table 4: Relative approval rate of thin file personal loan applicants compared to credit-experienced applicants

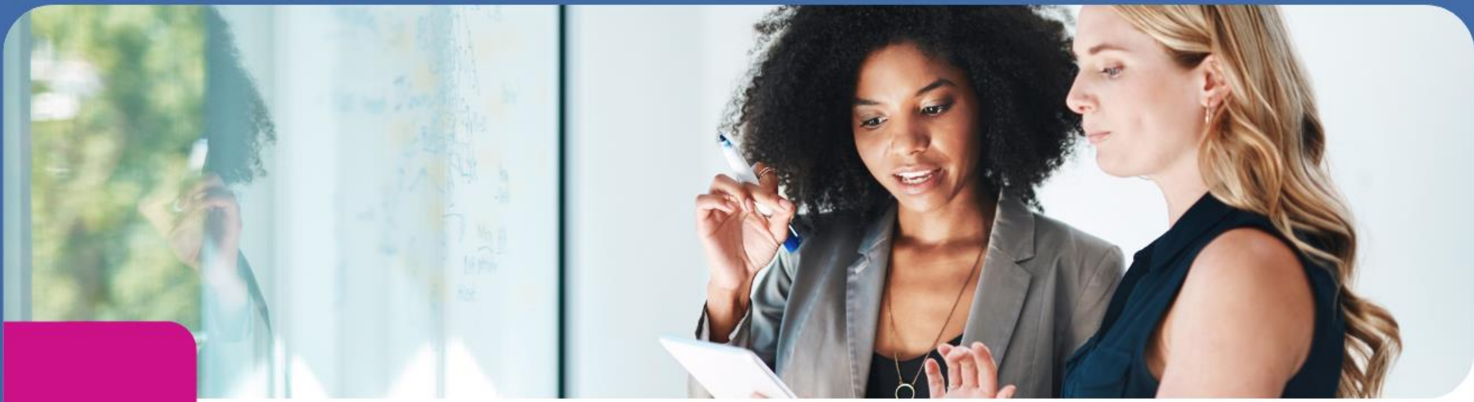
Difference in accept rate	Thin file group 1	Thin file group 2
'Big 4' banks	-23%	-13%
International banks and prime non-bank lenders	-54%	-24%
Regional banks	-55%	-39%
Near-prime lenders	-69%	-56%

Where a consumer had a rudimentary credit history (i.e. one account at some point in the last 2 years, but no credit currently) the disadvantage was generally lower. Interestingly, when applying with the 'Big 4' banks, consumers with a rudimentary credit history had only a moderately lower likelihood of being declined than their 'experienced credit' counterparts (i.e. 13% lower). This potentially suggests that the combination of some credit history together with a substantial savings and banking transaction record with that deposit-taking bank was used when assessing a person's credit risk.

As such, we believe that banks that have access to a customer's income, savings and expenditure history (i.e. their financial footprint) are better able to accurately predict a consumer's credit risk than other lenders. Banking transaction data offers a window into financial and credit stability – both where credit data is absent and as an adjunct to credit bureau data.

Questions to consider – diagnosing approval gaps

Where are approval gaps most pronounced for thin file applicants – by product, channel, or risk band – and what is the likely mix of serviceability constraints versus limited behavioural visibility driving those outcomes?



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Case study – what was tested

To this point, we have shown that thin file applicants represent a sizeable portion of the credit-seeking population and that lenders are more likely to decline these applicants – particularly when they lack access to behavioural data. These observations set the foundation for the case study's core question – is it possible to effectively remove the barriers that currently prevent access to low-cost, prime credit?

The analysis used application and performance data from a major Australian near-prime lender, with credit outcomes observed 12 months after account opening. Credit performance was measured 12 months after account opening, with performance of thin file applicants compared to their credit-experienced peers.

How credit risk is assessed

Credit risk was assessed using observed bad rates 12 months after account opening. The study compares approval rates achievable when controlling for the desired bad rate, and bad rates achievable when controlling for the desired approval rate.

Scoring strategies evaluated

The case study evaluated four strategies:

- **Internal application score** – based on demographic, geographic and self-reported financial information
- **Experian's Consumer Risk Score (CRS)** – based on credit demand and limited credit holdings and delinquency data
- **Experian's Transaction Risk Score (TRS)** – based on detailed banking transaction data, including:
  - Income regularity and trends
  - Expenditure volumes, categories and patterns
  - Payment methods – customer-initiated vs bank-controlled (e.g. direct debits)
  - Payment velocity and bill payment consistency
  - Cash withdrawals and traceable transactions
- **Combined strategies** – using multiple data sources (e.g. application data + TRS, CRS + TRS)

Decision lenses

- **Fixed bad rate** – how many thin file applicants can be approved at a given risk threshold (e.g. 2.8% or 2.0% at 12 months)
- **Fixed approval rate** – what bad rate results when approval volume is held constant (e.g. 48% at 12 months)

Before comparing how different scoring approaches perform for thin file applicants, we first establish the cohort's observed credit risk 12 months after account opening, relative to credit-experienced peers.

Baseline risk observation

At 12 months post-acceptance, the bad rate for thin file consumers was 4.3%, compared to 2.8% for credit-experienced consumers – **a 50% higher risk.** This confirms that thin file consumers, as a group, are riskier and cannot be universally approved.

Case study results – what changed when transaction behaviour was included

The case study revealed three clear shifts in outcomes when transaction behaviour was included:

At the lender's benchmark risk level, transaction behaviour supports higher inclusion

What we observed (12-month outcome): Using TRS, **74%** of the lender's approved thin file customers were found to have a similar credit risk to credit-experienced counterparts at the 2.8% bad rate benchmark. Using the lender's internal application score, the comparable proportion was 38–50%.

What this means for decisioning: At a defined benchmark risk level, banking transaction behaviour can identify a larger share of the approved thin file population that sits within that benchmark, improving confidence in who falls above and below the risk threshold.

Question to consider

At your benchmark bad rate, how much thin file volume is being constrained by limited visibility rather than your risk appetite?

Holding approvals constant, outcomes diverge materially

At a fixed approval rate of 48%, the observed 12-month bad rate was:

- 2.0% using TRS
- 2.8% using CRS

That is a **28% lower bad rate** for the same approval volume when using transaction behaviour.

What this means for decisioning: If volume is the constraint (growth targets, capacity, or policy settings), transaction behaviour changes the risk outcome without changing approvals, which can reduce losses and downstream collections effort at the same throughput.

Combining signals delivered the strongest result

What we observed at a 2.0% bad rate threshold:

- CRS alone: not achievable
- TRS alone: 48% approval of thin file consumers
- CRS + TRS: 62% approval of thin file consumers

At a fixed 48% approval rate, observed bad rates were:

- 2.8% using CRS alone
- 2.0% using TRS
- 1.6% using both data sources together

What this means for decisioning: Where policy design allows, a combined approach can improve inclusion and reduce risk simultaneously, rather than forcing a trade-off.

Using both data sources together showed a **43% reduction** in bad rates compared to using credit bureau data alone at the same approval rate (48%).

Results are calculated on approved accounts only — rejected applications are omitted. "Through-the-door" estimates apply a conservative assumption that previously rejected applicants remain unapproved, and this assumption is applied consistently across comparable results.

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Behavioural drivers – what transaction data reveals when credit history is limited

Why banking data is so predictive

Having demonstrated that banking transaction data is a highly effective tool for identifying the credit risk of thin file applicants, we explored the behavioural drivers leading to this result.

The predictive strength comes from the ability to profile a consumer's financial activity and spending priorities – particularly as these behaviours shift across different economic conditions. When modelled effectively, transaction data can show the relationship between a person's financial decisions and their likelihood to manage credit responsibly.

Everyday behaviours that signal creditworthiness

Many of the behaviours associated with lower credit risk are evident in how individuals manage their day-to-day finances. Banking transaction data captures these behavioural signals by revealing patterns such as:

- How does a person prioritise their spending when choices must be made?
- How prudently does the consumer manage their money and how consistently do they do this?

When modelled effectively, transaction behaviour can show the relationship between a person's financial decisions and their likelihood to manage credit responsibly – for example, whether they tend to prioritise financial obligations over discretionary spending. Through Open Banking, lenders gain visibility into these behaviours, enabling more informed and inclusive decisions to be made.

Traits of lower-risk thin file consumers

From the case study, lower-risk thin file consumers typically demonstrated the following behaviours:

- Maintaining a consistent positive account balance, avoiding overdrafts
- Receiving regular income, even if not high, paired with responsible financial habits
- Making regular payments on essential services, such as telecommunications
- Using direct debits and ensuring sufficient funds are available for meeting scheduled payments
- Preferring electronic payments over frequent or large cash withdrawals

Traits of higher-risk thin file consumers

By contrast, higher-risk consumers were more likely to:

- Make frequent ATM cash withdrawals
- Incur account fees
- Miss or delay payments on recurring bills, such as phone services

In essence, transaction data translate everyday financial behaviours – such as budgeting, payment discipline and spending visibility – into indicators of creditworthiness.

For thin file applicants, these behavioural insights offer a meaningful way to demonstrate financial reliability and help lenders make more confident decisions when credit files are thin.

5 Implications for strategy and policy design

Data asymmetry can limit fair and efficient credit decisioning, particularly for thin file applicants where credit file visibility is limited. For lenders, this creates a strategy and policy design challenge: how to set cut-offs, pricing tiers, referral rules and review pathways when traditional credit signals are thin.

In Australia, around 1 in 5 consumers who apply for credit with a mainstream lender have limited credit history visible to that lender, and approval likelihood is typically 20–50% lower than for credit-experienced consumers (varying by lender type and product risk profile).

The findings show lenders are less likely to disadvantage thin file consumers when they have access to banking transaction data. These outcomes are driven by two factors:

- Coverage – transaction data is available across the full spectrum of consumer profiles, including those with limited or no credit history
- Behavioural insight – it reflects real-world financial management behaviours aligned to creditworthiness

Together, these factors create practical levers for strategy and policy design in thin-file segments. The questions below highlight where incorporating transaction behaviour can tighten decisioning controls while maintaining disciplined policy thresholds.

- **Funnel impact –** When credit history is limited, where does uncertainty most influence outcomes in your funnel – the cut-off, pricing outcomes, or the path to manual review?
- **Segment concentration –** How does the prevalence of thin-file applicants vary across your products and acquisition channels?
- **Process design –** Where do you currently apply additional steps (manual review, documentation, conservative pricing) to manage uncertainty?
- **Decision levers –** Where would improved behavioural visibility change your decision approach most – expanding approvals in specific risk bands, reducing referrals and exceptions, or sharpening pricing and limit setting?
- **Policy design –** How will you design guardrails and monitoring for thin file decisions so performance is measurable and policy changes are explainable to internal stakeholders?

Conclusion

Banking transaction data can offer a more accurate view of consumer risk, enabling a more inclusive credit approval process for thin file applicants. Used on its own or alongside other data sources, it can support fairer access to mainstream credit while maintaining disciplined risk guardrails.

In the case study, incorporating transaction behaviour alongside credit bureau data was associated with:

- Higher-confidence inclusion at benchmark risk – 74% of approved thin file customers aligned to the lender's benchmark risk level (comparable to credit-experienced customers)
- Risk reduction – 43% reduction in risk versus credit bureau data alone at the same approval rate
- Lower bad rates – 28% lower bad rate versus credit bureau data alone at the same approval volume

Together, these results show how transaction behaviour can help lenders make more confident decisions for thin file applicants – balancing inclusion with strong risk outcomes.

Meet the author

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Michael has more than 30 years' experience in credit risk analytics and research, supporting the banking, finance, telecommunications and utilities sectors. He has delivered strategic consulting and advisory services and developed data-driven solutions for credit origination, customer management and collections for leading financial institutions in Australia and throughout the Asia-Pacific region, as well as in South Asia, the United Kingdom, Switzerland and Canada. His work spans secured and unsecured consumer credit as well as SME and broader commercial lending.

Michael has also provided advisory services to the credit information and reporting sectors in Australia, New Zealand, China, Hong Kong, Indonesia and Korea. As part of broader strategic engagements, he has worked with organisations such as the IFC (World Bank) in South Asia and South-East Asia, the Ministry of Finance (Thailand) and the Central Bank of Indonesia.

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