Credit Impacts of More Comprehensive Credit Reporting in Australia and New Zealand

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PERC

RESULTS AND SOLUTIONS

Acknowledgments

PERC wishes to thank Dun & Bradstreet Australasia for their generous financial support for this project, without which completion would have been impossible.

In addition, many staff and Dun & Bradstreet Australasia provided insights and assistance that greatly enhanced the quality of this report, including: Paul Bracewell, Steve Brown, Christine Christian, Bridget Dixon, Damian Karmelich and Sally Liu. PERC is also grateful to Clark Abrahams and Sunny Zhang for feedback and input on technical matters relating to credit risk assessment, credit scoring, and working inside the credit black box.

Finally, we wish to thank Whytney Pickens for her invaluable administrative and editorial assistance with this report.

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Key Findings

Since April 1, 2012 creditors in New Zealand have been able to report additional account information to credit bureaus. Generally this includes the type of account, account payment status, and whether an account is open or closed—although there are some minor but important differences between what is in place in New Zealand and what is under consideration in Australia. These are addressed in the body of the report.

Despite strong evidence from analysis in other economies, the issue of the likely impacts of credit reporting reform in Australia and New Zealand has never before been assessed using actual data from either of these markets. This report summarizes the results from a pioneering joint undertaking by PERC and Dun & Bradstreet using credit data from 1.8 million Australians.

The results of this analysis provide strong empirical support for the proposed credit reporting reform in Australia, and the reform that took effect in New Zealand as of April 2012. Key findings are below.

▸ Credit Reporting Reform Will:

○ Create Growth in Lending to the Private Sector— Using a target default rate of 3%; an additional 34% of applicants could be accepted with fair file data. This represents a 70% increase in acceptance at that default rate and results from a greater capacity to identify high risk and low risk borrowers. At a 4% default rate, acceptance could rise 27% without increasing defaults. Fewer lending errors are made and lenders will be able to make more credit available.

○ Make Lending Fairer — Groups that have traditionally had greater difficulty accessing affordable sources of mainstream credit will see a significant increase in credit access. At a 4% default rate, while total acceptance rises 27%, and rises for all age groups, it rises the most for the younger borrowers. For instance, borrowers between 18 and 25 witness a 46% increase in acceptance and those between 26 and 35 witness a 42% increase.

○ Help Lenders Mitigate Against Risk — Because lenders have an increased ability to distinguish between high risk and low risk borrowers, loan portfolio performance can improve dramatically. For a 60% target acceptance rate, the default rate or bad rate for the negative only model would be 3.5%, while the default rate or bad rate for the fair file model would be only 1.9%. That is, the share of bad loans falls by 45% when fair file data is included in the decision.

▸ Lenders Benefit from Sharing Positive Data with Credit Bureaus —

Access to new markets and better portfolio performance are made possible only by using new value added services, including credit bureau scorecards with highly predictive positive variables. The sooner fair file data comes online, the better individual lenders are able to identify over-extended borrowers, manage the transition from negative only to fair-file, and to experience growth in new markets and improved portfolio performance.

▸ Non-Financial Account Data is Valuable for Credit Risk Assessment—

While energy utility and telecommunications firms have long been using credit report information for eligibility determination, lenders in Australia and New Zealand can benefit from using non-financial account information for credit risk assessment. Scorecard performance, as measured by the Gini coefficient, rose 16% when fair file telecommunications account information was included. The result of this was to increase acceptance by 20% at the target default rate of 3% for those borrowers with fair file telecommunications account data reported.

▸ A More Comprehensive System is a More Forgiving System — In the current, primarily negative only credit reporting system of Australia, borrowers who have had serious credit mistakes in the past are virtually excluded from access to credit for the five to seven years that the derogatories remain on their credit files. This is due to the reality that there is no positive data (such as recent on-time payments) to counter balance the past negative data. With fair file data, credit access for those with past credit mistakes improves. Among those with a previous bureau derogatory, acceptance rises from 0% to 6% at a 4% default rate and from 0.3% to 28% at a 6% target default rate.

▸ Customer/Consumer Education is Vital to Realize Benefits — Owing to the relatively lengthy period during which a negative only credit information sharing system has been in place in Australia and New Zealand, creditors would do well to educate their customers of the benefits from the increased information sharing with credit bureaus. As credit reporting is designed to affect individual behavior, without borrower knowledge of the consequences of the reform, the change in their behavior is likely to be more limited and the system will not fully capture the benefits of reform.

▸ Findings Consistent with International Evidence — The findings presented in this paper are broadly consistent with international evidence and experience that more comprehensive credit reporting (specifically, shifts from negative-only to full-file reporting) result in more lending, better lending, and fairer lending. Also consistent with the international evidence, non-financial account data, specifically telecommunications account data, is found to be valuable in risk assessment.

1. Introduction

Credit information sharing reform efforts have been underway in Australia and New Zealand for the previous eight years, and by some measures even longer—potentially just after the 1988 Privacy Act. The last few years have seen progress in both countries.

In May 2008, the Australian Law Reform Commission (ALRC) issued a final report to the Attorney General, including support for a limited reform in credit information sharing. Then, in October of 2009, the Australian Government issued a response to the ALRC final report, including support for proposed reforms that would permit creditors to report additional data elements to one or more licensed credit bureaus including, account type, date account opened, and account payment status (whether the account is current, 30+,60+, or 90+ days beyond term).

The Australian Government's legislative changes, reflecting its response to the ALRC's privacy inquiry, is currently before Parliament. In March 2011 the Office of the Privacy Commissioner made a submission to the Senate Committee on the draft credit reporting provisions. The Senate Committee has released reports into the draft Australian Privacy Principles and the draft credit reporting provisions, each of which make a number of recommendations.[1]

In New Zealand, owing to the absence of a need for legislative reform, the Privacy Commissioner—after a series of deliberations—took measures to permit greater, but limited, credit information sharing reform. These reforms took effect on 1 April 2012. The Office of the Privacy Commissioner has also reaffirmed its commitment to revisit the issue of further incremental reform within a reasonable period of time after the initial reform, and will likely give serious consideration to the consequences of the initial reform when considering further change.

Dun & Bradstreet collected a sample of depersonalised application, payment and performance data from creditors - including the five additional fields under consideration—to conduct research and test potential value added services. Toward that end, Dun & Bradstreet contracted with the Policy and Economic Research Council (PERC). PERC is a U.S. based public policy research institution with a particular expertise in credit information sharing reform. PERC also has the quantitative skills and experience to construct fair-file scorecards and demonstrate the impacts on firm level portfolio performance, lending to the private sector, and credit access by varying social demographic cohorts. This report reflects the results of that effort

[1]The recent chronology of developments surrounding credit reporting reform in Australia was downloaded from: http://www.privacy.gov.au/law/reform

2. Negative to Full-File Credit Reporting: A Global Perspective

Credit reporting helps solve the problem of information asymmetry between borrowers and lenders[2]. However, the degree to which credit reporting actually helps solve this lending problem depends on the details of the credit reporting. Generally, greater sharing of credit information correlates with sustained growth in lending to the private sector, and resultant increases in Gross Domestic Product (GDP), productivity, and capital accumulation[3]. Wider credit reporting has also increased fairness in lending, owing largely to the greater ability of consumers to rely on their credit and repayment history rather than assets as collateral. And the reporting of more information on more accounts enables greater use of scorecards and automated underwriting that reduces the human bias associated with manual underwriting. As a result, the expansion of credit reporting has effectively enabled groups of borrowers that have traditionally faced systemic bias to more easily access affordable mainstream credit[4].

The current practice of credit reporting in Australia can best be described as negative only. However, this is not to say that all information collected and exchanged is 'negative' from the perspective of the borrower. For instance, the number and type of credit application enquiries, as well as borrower age and number of addresses recorded, is exchanged. But the most important (information rich) variables collected are negative, such as information on defaults and bankruptcies. These are sometimes referred to as "negative-event based data". That is, a bureau would receive information regarding an account only if there is a negative event, such as a default.

Full-file credit reporting, on the other hand, includes negative data as well as 'positive' data. Positive data elements are usually reported to a credit bureau from data furnishers on a monthly basis, no event (positive or negative) is needed. These include whether an account is open or closed, who closed it (bank or borrower), credit limits, outstanding balances, and timeliness of payments (on-time, 30 days late, 60 days late, etc.).

A common assumption among participants in a negative-only system is that lenders only need to know of serious delinquencies on an applicant's other accounts to make an effective credit decision. The limitations of

[2] For a theoretical consideration, see Joseph E. Stiglitz and Andrew Weiss, "Credit Rationing in Markets with Imperfect Information," American Economic Review, vol. 71, no. 3 (June 1981): 393-410. Also see Marco Pagano and Tullio Japelli, "Information Sharing in Credit Markets," Journal of Finance (December 1993): 1693-1718; and Dwight Jaffee and Thomas Russell, "Imperfect Information, Uncertainty and Credit Rationing," Quarterly Journal of Economics, vol. 90, no. 4 (November 1984): 651-666. See also essays from Margaret Miller, ed., Credit Reporting Systems and the International Economy (Cambridge, MA: MIT Press, 2002). There is also an extensive literature on the positive effects of greater lending to the private sector. See, e.g., Ross Levine, "Financial Development and Economic Growth: Views and Agenda," Journal of Economic Literature, vol. 25 (June 1997): 688–726; Jose De Gregorio and Pablo Guidotti, "Financial Development and Economic Growth," World Development, vol. 23, no. 3, (March 1995): 433-448; J. Greenwood and B. Jovanovic, "Financial Development, Growth, and the Distribution of Income," Journal of Political Economy, vol. 98 (1990) :1076-1107.

[3] Michael Turner et al., On the Impact of Credit Payment Reporting on the Financial Sector and Overall Economic Performance in Japan (Chapel Hill: Political and Economic Research Council, 2007). Also see Simeon Djankov, Caralee McLiesh, Andrei Shleifer, "Private Credit in 129 Countries." NBER Working Paper no. 11078 (Cambridge, MA: National Bureau of Economic Research, January 2005), available at http://papers.nber.org/ papers/w11078.

[4] For evidence and measures of increased credit access, see Michael Turner, The Fair Credit Reporting Act: Access, Efficiency, and Opportunity. (Washington, DC: The National Chamber Foundation, June 2003)

such assumptions, however, are considerable. First, this approach does not capture moderately late payments (30+, 60+, or even 90+ days past due). Yet, these late payments, although perhaps short of an actual default, are often telling indicators that a borrower may be seriously late with future payments. That is, minor delinquencies are often predictive of later, more major delinquencies (such as actual defaults and bankruptcies). Thus, the inclusion of these moderate delinquencies can improve lending decisions.

Second, negative-only reporting overlooks positive on-time payment information, which offers a low-cost method of gathering data on applicants who have paid in a timely fashion. Without this information, it may not be possible to distinguish an applicant with no accounts (and no derogatories) from an applicant with accounts and only on-time payments. On-time payment data provides information on those who may otherwise be shut out of the market, such as lower-income borrowers, women, racial minorities, and the young. Reporting positive information not only expands access, but it also creates fairer access to credit simply because more information allows lenders to make more informed decisions and not ration credit. Evidence also suggests that full-file reporting deters discrimination because loan denial to qualified applicants who are members of underserved communities becomes more difficult to justify.

Third, full-file reporting allows creditors to determine how many lines of credit a potential borrower already has and, in many cases, the associated balances and credit limits. This enables the creditor to better gauge the potential borrower's credit capacity and true level of indebtedness, thereby reducing the chances of extending too much credit, resulting in over indebtedness. Therefore, broader information reporting is an important protection against credit overextension or over indebtedness.

Moreover, greater information allows lenders to speed loans along, especially if lenders use automated decision systems, such as statistical scoring models. More information also lowers the costs of issuing a loan. Automated mortgage underwriting, enabled by full-file information, saved American consumers more than $18 billion in 2002[5]. In competitive credit markets, these savings are passed along directly to borrowers. Each of these operating logics means that more information leads to:

a. better predictions confirmed by better portfolio performance;

b. wider lending validated by larger acceptance rates; and

c. fairer lending in the sense that the composition of borrowers begins to more closely reflect the general population.

2.1 Global Evidence

There have been two primary approaches to assess the impact of credit sharing regime shifts from negative-only to full-file credit reporting. The first uses cross-national analysis, usually regression analysis, to determine how economy-wide lending levels, GDP growth, inequality, and other macroeconomic indicators vary with different types of credit reporting environments. In general, it is found that more information rich credit reporting environments (such as full-file compared to negative-only) are associated with increased lending to the private sector, which is associated with greater economic growth and reduced inequality[6].

However, associated with is different than being caused by. It could be that a more comprehensive credit-reporting environment is simply related to a more developed financial sector (in other ways), and it is these

[5] Michael Turner, The Fair Credit Reporting Act: Access, Efficiency, and Opportunity (Washington, DC: The National Chamber Foundation, June 2003), p. 8.

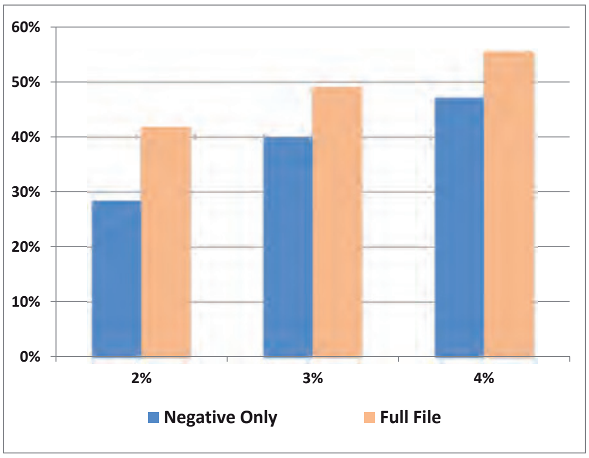
other factors that are really driving the increased lending. To understand better the cause and effect of how (and to what degree) more information leads to more and better lending, a microeconomic approach has been taken. This approach simulates individual lending decisions based (usually) on two sets of data. In this way, one can determine which set of data, such as negative-only or full-file, produces better lending decisions and would result in more lending.

Several simulations from several different economies have been produced to gauge this credit impact. Some elements of the credit file are kept while others are purged, thereby mimicking the information content from more restricted cases. The researchers then apply decision (credit scoring) models to the two (or more) sets of files. Thus for a simulation of negative-only reporting, positive information is purged. The scores produced are predictions of the likelihood of serious delinquency, bankruptcies, and other outcomes. The predictions are then compared with actual outcomes in the "observation" period, the year or years following the timing of the score.

The results of these simulations consistently show a substantial improvement in the ability of lending systems to predict good lending risks from bad lending risks when shifting to full-file data from negative-only data.

For instance, Barron and Staten, using US data, compared the findings of a simulated negative-only reporting system with a full-file, comprehensive system and found that for a 3% default target, a negative-only reporting system accepts 39.8% of the applicant pool, whereas a full-file system would accept 74.8% of the pool[7].

Figure 1: Acceptance Rates at Different Target Default Rates (US)



Source: Michael Turner et al., The Fair Credit Reporting Act: Access, Efficiency, and Opportunity, June 2003.

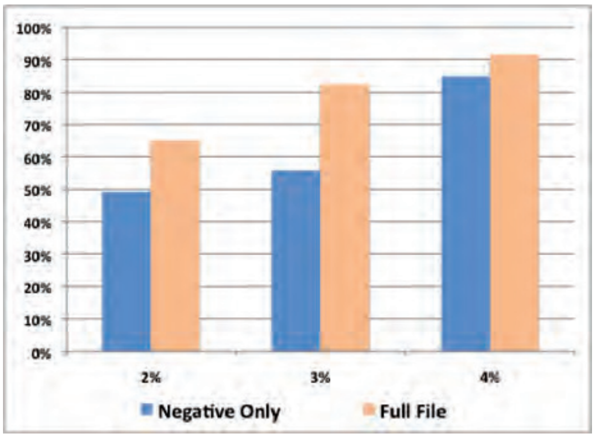
Figure 1 shows results from a similar simulation, also for the US, carried out by Turner et al. Again, for a given target default rate, lending can be expanded when lenders have access to greater information on borrowers. Figure 2 shows results from simulations using credit files from Brazil. While the numerical levels (acceptance rates) differ, the general qualitative story remains the same. Access to more information, shifting from negative-only data to full-file data, has the potential to improve and expand lending.

Importantly, these results also show that the credit impacts from improved information sharing can be quite large. They indicate that a shift from negative only to full-file reporting would likely result in sizable lending and economic impacts. Which is precisely what has been seen in the macroeconomic analysis.

[6] See Simeon Djankov, Caralee McLiesh, Andrei Shleifer, "Private Credit in 129 Countries.", Michael Turner and Robin Varghese, "The Economic Impacts of Payment Reporting in Latin America"
PERC, May 2007, Michael Turner, Robin Varghese, and Patrick Walker "The Structure of Information Sharing and Credit Access: Lessons for Policy," PERC, July 2008, and Thorsten Beck, Asli Demirguç-Kunt, and Ross Levine, "Finance, Inequality and the Poor," NBER, January 2007.
[7] Barron, John M. and Michael Staten. "The Value of Comprehensive Credit Reports: Lessons from the U.S. Experience," in Margaret M. Miller ed., Credit Reporting Systems and the International Economy. Cambridge, MA and London, England. The MIT Press. 2003.

These results are likely not surprising when one considers they are comparing scenarios in which lenders have access to very limited information such as past defaults and bankruptcies in the negative-only case and much more valuable information in the full-file case, such as recent payment behavior (short of defaults), debt levels, and the share of available credit being utilized.

Figure 2: Acceptance Rates at Different Target Default Rates (Brazil)



Source: Giovanni Majnoni, Margaret Miller, Nataliya Mylenko and Andrew Powell, "Improving Credit Information, Bank Regulation and Supervision." World Bank Policy Research Working Paper Series, No. 3443 (Washington, DC: World Bank, November 2004).

The second, equally as interesting part of the story deals with which borrowers benefit most from the increased information sharing. As seen in Table 1, Turner et al. found that it was those groups that were most underserved by the lending system which benefited the most from an increase in information available to lenders. In the case of the US in their 2003 study, ethnic minorities, the young, and members of low-income households benefited the most.

This was also found in a later publication by Turner et al. in which the impact of adding telecommunications and utility payment data was found to improve overall lending but would disproportionally increase lending to members of lower income households, minorities and the young[8].

Simulation results using credit files from Colombia also show this pattern. Acceptance rates among female borrowers and young borrowers increased more than average with the shift from negative only to full-file. Other socio-demographic variables, such as income, were not available for segmentation analysis in the Colombia simulation[9].

[8] Turner et al., "Give Credit Where Credit is Due: Increasing Access to Affordable Mainstream Credit Using Alternative Data." PERC, 2006.
[9] Michael Turner and Robin Varghese, "The Economic Impacts of Payment Reporting in Latin America" PERC, May 2007.

Table 1: Socio-demographic Impacts from Shift to Full-file Reporting from Negative-only Reporting (3% target Default Rate, US Data)

	Negative-only (index = 100)	Full-file
Race-Ethnicity		
Caucasian, Non-Hispanic	100	121.8
African American	100	127.9
Latinos	100	136.8
All Minority	100	135.5
Age		
<36	100	147.1
36-45	100	121.8
46-55	100	121.2
56-65	100	119.8
66-75	100	117.9
76+	100	119.9
Household Income (US$)		
< 15,000	100	135.9
15,000-29,000	100	129.7
30,000-49,000	100	124.2
50,000-99,000	100	120.6
>100,000	100	117.8

Source: Michael Turner et al., The Fair Credit Reporting Act: Access, Efficiency, and Opportunity (Washington, DC: The National Chamber Foundation, June 2003).

These results are consistent with macroeconomic research suggesting that greater information sharing and a more developed financial system are associated with increased economic equality.

3. Fair File Credit Reporting Project

3.1 Analysis Description

Dun & Bradstreet has been operating in Australia since 1887 and in New Zealand since 1903. For much of its history, it has focused on business credit reporting. Today it holds information on more than 2.8 million businesses in Australia and New Zealand. In 2004, it moved into the consumer credit report space and rapidly built its consumer credit database. Today, it is one of the two primary consumer credit bureaus in Australia, maintaining over ten million active accounts, representing a near universal coverage of over 95% of all credit active Australians [10].

PERC and Dun & Bradstreet Australasia began collaboration on the fair file credit-reporting project in 2009. The project is referred to as a fair file project since it is examining the impact of adding some positive data but not all positive data seen in the most comprehensive full-file systems, such as account balances. We coined this intermediate stage between negative-only reporting and full-file reporting simply as fair file reporting. The impetus for this project was to prepare for the anticipated shift to fair file reporting in Australia and New Zealand.

[10] Company information from interviews and http://dnb.com.au/Header/About_Us/index.aspx

Dun & Bradstreet partnered with a number of major lenders in Australia and a telecommunications firm. These were the positive data providers for the experimental database Dun & Bradstreet created for the project. These data providers supplied one and a half to two years of positive information (such as timeliness of payments) on individuals who had applied for credit between March 2008 and August 2009. As this represented more than 10 million applications, far more records than needed, an approximately one in three sample was used. As the sample size was reduced prior to all the data being merged, it was decided to include only those borrowers with birthdays on a day of the month that is evenly divisible by three. This includes the third of the month, the sixth, and so on.

This data was then merged together on the level of the individual and with the traditional negative-only bureau data from Dun & Bradstreet. This process, in and of itself, was a major undertaking as there was not available a single, primary, and unique identification number, such as the Social Security number in the US. The lack of a unique universal identifier required that we merge the records on a constellation of data elements such as name, date of birth, and address. Dun & Bradstreet, which is a world leader in record matching, took on this task.

Another aspect of the project, maintaining privacy and security, meant that records with personally identifiable information (such as name and date of birth, needed for matching) could not be exchanged. Instead the data was transformed into coded values (hash values) using a hash algorithm. In this way, for instance, Smith was not merged with Smith, but the hash value of the word Smith was merged with the hash value of the word Smith. Thus, the data merge could occur without using personally identifiable information. One complication of this is that if there is any discrepancy between the data in a record, no merge will occur. For instance, if the name of a street is Green Leaf Way in one record and Greenleaf Way in another record, no match would occur. To account for this inexactness in the records, several versions of the data (used in matching) were used and had hash values created. For instance, all words were converted to uppercase letters but one version included spaces, and another removed all spaces (as with the previous example). For names, such as surnames, first names, and street names, a Soundex version of the word was also created. So, Katelyn, Caitlin, and Kaitlyn have the same phonetic sound and would have the same Soundex value. As such, some inexactness in the data could be tolerated in the matching. Thus, the database was assembled without exchanging personally identifiable information and accounting for imperfect data.

After we reduced the sample size and merged the data, we were left with a database containing records based on approximately three million credit applications. One application was randomly chosen from each individual that had multiple applications. This reduced the sample to 1.8 million records from (unique) individuals that submitted credit applications between March 2008 and August 2009.

The database we created contains close to two million records, drawn from a pool of applications with a very wide coverage of the Australian credit active population. The resulting sample had a very small margin of error, allowing for very precise measurements. For a sample size of 1000, the margin of error would be around 3%. For our sample size of 1.8 million, the margin of error is 0.07%. Differences between the results presented here and those that would be obtained a few years after positive data began to be exchanged would more likely be due to changes in other aspects of the data and lending environment (such as changes in borrower or lender behavior or macroeconomic conditions) than due to the sample size used.

The fair file experimental database that was created had both negative data and positive data elements (expected to be reported in the future) and, thus simulated the expected full-file data environment. Credit outcomes were observed over a 12-month period following the application for credit. A record would then be flagged as a good if in the 12 months following an approved application, there were no bureau derogatories (defaults, judgment, bankruptcy, etc.) or any payment that was 60+ days past due. Bads were records with a bureau derogatory or a payment 90+ days past due in the 12 month observation window[11].

Two credit scoring models were built on this dataset. One was developed using only the negative-only data currently available in Australia. The second was built using all available data elements in the database. This second model is the fair file model.

The base or negative only model contained two score cards, one for shallow files (fewer than three enquiries in the past 60 months) and one for deep files (3+ enquiries in the past 60 months). The fair file model contained three score cards: (1) a negative-only card for files with no fair file data, (2) a positive thin-file card for files with fair file data and 0 or 1 opened or recently closed accounts reported, and (3) a positive thick-file card for files with fair file data and more than 1 opened or recently closed accounts reported.

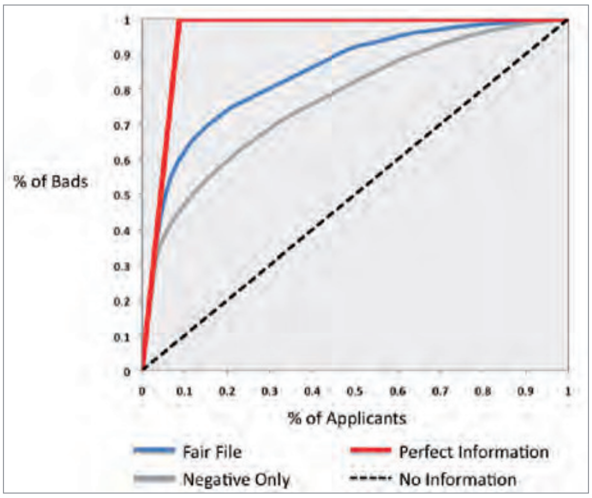
We then compared performance (ability to predict bads and goods) of these two models along several dimensions. In what follows, we detail the results of these comparisons, focusing on presenting findings based on the so-called known goods and bads (KGB). By this we simply mean how well the models predict the goods and bads actually observed as defined above. To include the rejected and other non-good-bad records in model development, these records were assigned to be goods and bads based on the available data. The credit scoring models we used were initially created with the records that were known to be good or bad (known goods and bads). We then scored records that could not be determined to be a good or a bad, for instance, a record based on a credit application that was rejected and which did not have any outcomes that would make it a bad, with these models. We then converted these scores to probabilities of being bad. These records were then assigned good or bad based on these probabilities.

While this makes sense in model development (so all records can be included), it is sometimes more convincing to see how models predict actual outcomes as opposed to assigned/estimated outcomes. It should be noted that there is little qualitative difference between the results based on KGBs and all records.

3.2 Basic Results

There are several ways to compare and describe credit scoring models and their performances. They describe how well models identify goods from bads. However, there is no single, perfect way of measuring model performance.

Figure 3: Cumulative Accuracy Profile (CAP) Curves (Known Goods and Bads)



[11] These definitions produce records that are neither good or bad, these are reject application, withdrawn applications, and those with payments between 60 and 90 days past due. These records entered into the analysis via reject inference.

This is not only the case since no index number perfectly captures all aspects of a model but also because different users of the models have different needs for the models. For instance, one user may be more interested in how the models perform in the subprime segment than in the prime segment. Nonetheless, what is presented here are the standard measures of model performance.

Figure 3 shows the cumulative percent of bads captured for the percent of applicants with the lowest scores. If no information was used, then the bottom 10% of applicants would contain 10% of the bads, the bottom 20% would contain 20% of bads, and so on. This is precisely what the 45 degree dashed line describes. The red line describes the other extreme case, the case where perfect information is available that perfectly predicts who will be a good and who will be a bad. Since the rate of bads was about 9% in this sample, a perfect model would capture 100% of the bads in the bottom 9% of applicants. That is, all the bads are at the very bottom.

Using information that is less than perfect produces results somewhere between these two extreme cases. The base, or negative only, case is shown by the gray line. This model does a respectable job in predicting goods and bads. For instance, about half of bads are found among the 10% of applicants with the lowest scores.

The addition of the fair file data elements produces a far more accurate model, this is seen in the blue line in figure 3.

The proportion of the area between the red line and the dashed line that is under the blue or gray line is referred to as the Gini coefficient. So, a no-information model (the dashed line) would have a Gini coefficient of zero and a perfect model (the red line) would have a Gini coefficient of one. Table 2 provides the Gini coefficients and other model performance measures for the base (negative only) model and the fair file model.

Table 2: Base and Fair File Model Performance

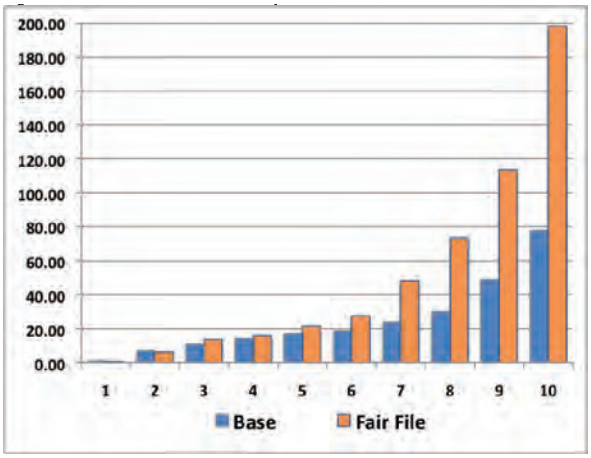
	Base (Neg Only)	Fair-File
Gini	.590	.759
K-S	.434	.594
% of Bads in Bottom 10%	47%	62%
% of Bads in Bottom 20%	60%	74%

(Known goods and bads)

Table 2 shows that the Gini rises from .59 to .76 when fair file data becomes available and the K-S statistics rises from .43 to .59. The K-S simply measures the greatest separation between percent cumulative good and percent cumulative bad. The percent of bads captured in the bottom 10% and 20% of applicants rises by about a third and a fourth, respectively.

Another more intuitive way to compare credit scoring models is to look at how well goods and bads are separated by deciles of the population (ranked by the scores).

Figure 4: Good-Bad Odds Ratios by Credit Score Deciles



This separation is typically expressed in terms of the ratio of goods to bads per decile. Figure 4 shows that with the fair file data elements, the top decile contains just about 200 goods for every bad. For this decile, the base case (negative-only) contains less than 80 goods per bad. The fair file model produces a much better separation of goods and bads in the upper deciles. It is also the case on the flip side. In the lowest two deciles, there are more bads relative to goods in the fair file model, although, it is hard to see in this graph.

To demonstrate that the superior performance of the fair file model is robust beyond the exact definition of bad, a narrower definition of bad is examined next. There are two reasons why this is important. First, the definition of bad used in this project includes accounts that were 90+ days past due (dpd), but not necessarily defaulted on, which is standard in fair file/full-file environments. Since this is a fair file variable, one may believe that the reason the fair file model is performing better is due to the fact that it is using fair file data to predict some fair file outcomes. Since both models have access to negative (base) data, we can look at the good-bad separation when the definition of bad is negative-only to determine if this is the case.

Second, since the negative 'bureau' definition of bad (default, bankruptcy, etc) is the traditional definition available and used in Australia and New Zealand, it is useful to show some results based on this definition.

However, there is one caveat: the models shown are the same models used above. As such, they were not optimized to predict this narrower definition of bad. Therefore, one would expect the actual separation shown to be not as great as could be achieved if the models were optimized for this definition of bad.

Figure 5: Good-Bad Odds Ratios by Credit Score Deciles, for Base Definition of Bad

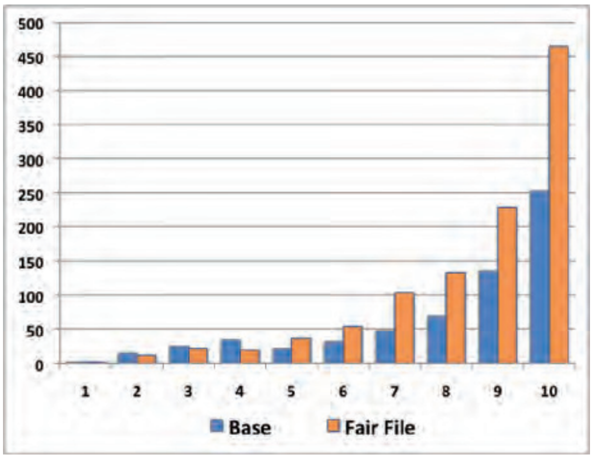
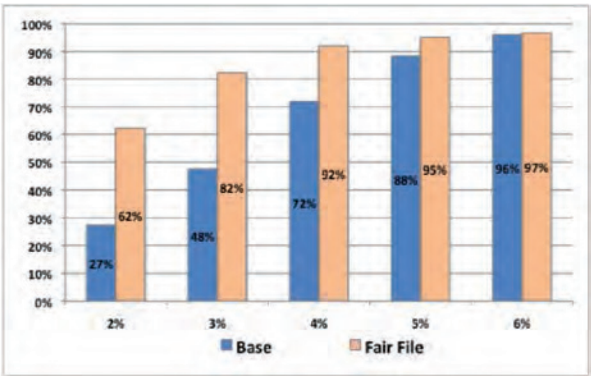


Figure 5 shows that for the base (negative only) definition of bad, the fair file model still strongly outperforms the base negative only model. This overall strong good-bad separation also suggests that the results are robust across particular definitions of goods and bads. The actual ratio values are higher in figure 5 than in figure 4, since without using the 90+ dpd criteria, there is a smaller proportion of bads, hence, the ratio of goods to bads is greater.

Figure 6: Acceptance Rates for Various Target Default Rates



From the perspective of the lender, what is of ultimate importance is total portfolio performance. If for example, a portfolio was made up of individuals that had credit scores above a certain cutoff, what is of concern is the total bad rate for individuals above this cutoff. Or, more realistically, a cutoff score is chosen so that the bad rate of all those at or above the cutoff is equal to a target default or bad rate. Whether one uses a more or less accurate underwriting method (scoring model) the bad rate will be the same. What will vary is the acceptance rate, the proportion of the applicants that can be accepted. This is because a more accurate scoring model will have fewer bads at the top of the score distribution and fewer goods at the bottom. So, more applicants can be accepted because fewer lending mistakes are made.

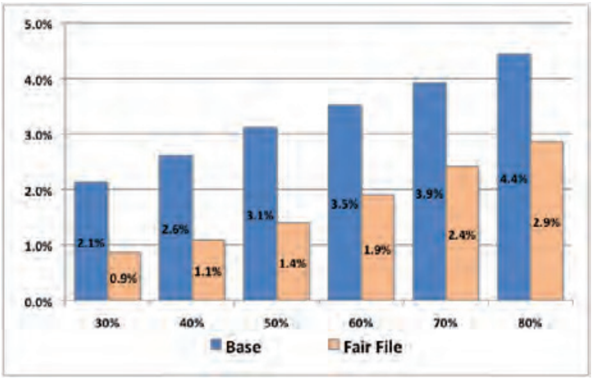
Figure 6 shows the difference in acceptance rates possible between the two models for given target default (bad) rates. What this reveals is that at a 3% default target, an additional 34% of applicants could be accepted with fair file data.

The counterpart to this is the default rate or bad rate for a given acceptance rate. For instance, if the top 60% of applicants were accepted using each model, what would the default or bad rate be for each of the models?

Figure 7 shows that for a 60% target acceptance rate, the default rate for the negative only model would be 3.5% and the target default rate for the fair file model would be 1.9%.

In a sense, these graphs show the different default rate-acceptance rate tradeoffs between the two models. Figure 6 indicates lenders could have the same default rate but have a much larger portfolio, and figure 7 indicates that lenders could have the same size portfolio but one with a much lower default rate. Of course, lenders in reality may choose some combination of a larger and better performing portfolio. It is even possible that some may prefer something outside these two cases, such as a higher target default rate, since a much larger portfolio may produce some economies of scale and better risk assessments may enable improved risk-based pricing.

Figure 7: Acceptance Rates for Various Target Default Rates

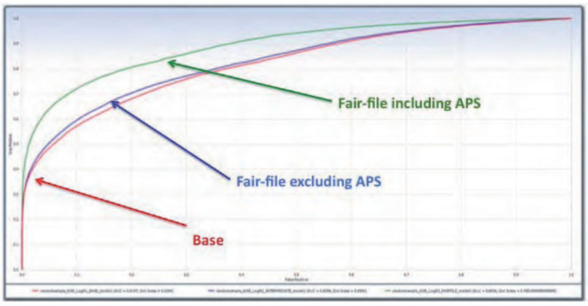


These findings are fairly consistent with simulations from other economies and cross-country analysis. This suggests that Australia and New Zealand should expect lending growth from greater information sharing.

3.3 Impact of Account Payment Status Variables

The fair file case included a number of fair file variables, including number of accounts open, number closed, types of accounts opened, applications approved and denied and so-called account payment status variables. Account payment status (APS) variables include data on the timeliness of payments, such as whether payments were on time, less than 30 days late, 30+ days late, 60+ days late, and so on. It is these payment history variables that are often the most valuable indicators of future payment outcomes in full-file credit reporting systems. It is often much more valuable to know how a borrower is managing accounts than to simply know that they have accounts (and of what type). To see what impact these APS variables had in the overall lift seen in the fair file model relative to the negative only model, we created a third intermediary model. This model excluded the account payment status variables but included all other variables.

Figure 8: CAP Curves Impact of Account Payment Status (APS) Variables



As can be seen in figure 8, there is only a slight improvement in model performance when the non-APS variables are added. It is the inclusion of the account payment status variables that account for most of the increase in model performance, relative to the negative-only base model, seen in the fair file model.

In fact, of all the variables available, including new fair file positive data elements and the current bureau data elements, the variables with the highest information indexes (those most predictive of goods and bads) were the timeliness of payment variables, that is the status of account payment. As such, it should not be a surprise that they alone could improve model performance so much.

3.4 Impact of Telecommunications Account Data

The dataset used in the analysis also contains data furnished from a telecommunications provider. The impact of this data can be assessed in a number of ways. As with the comparison of negative-only and fair file data, the most straightforward way to examine the impact from the telecommunications account data is to compare model performance with and without the telecommunications data. However, there are a few details that must be considered. First, not all records have telecommunications account data. So, if only a small share of records have any telecommunications account data, then the impact of the data will also be very small. Second, not all of the records with telecommunications account data have fair file (positive) telecommunications account data. As such, three comparisons were made. The first compared the impact of the inclusion of telecommunications data on all records. The second looked at the subset of records with any telecommunications data, and the third looked at the subset with positive telecommunications data. It is likely this last calculation is the most useful. This is the case since, given the widespread coverage of telecommunications and utility accounts across the adult population, most credit files could include some type of non-financial payment histories, such as telecommunications payments.

Table 3: Relative Fair File Model Performance with and without Telecommunications Account Data

Scenario	Fair File Model No Telecom Data (index=1.00)	Fair File Model With Telecom Data
All Scoreable Records	1.00	1.04
Records With Any Telecom Data	1.00	1.13
Records With Positive Telecom Data	1.00	1.16

As is seen in table 3, model performance (as measured by the K-S statistic) rises 4% among all records. Restricting the analysis to just those records with some telecommunications data shows a K-S rise of 13%. And finally, restricting the analysis to those records with positive telecommunications data shows that performance rises 16%. The result of these modifications was to increase acceptance by 20% at the target default rate of 3% for those borrowers with fair file telecommunications account data reported. These model performance rises are larger but of roughly the same magnitude when compared to the impact of including non-financial positive data in US credit files[12]. In the US case, the rises in the primary model considered were between 1% and 8%, depending on the particular population examined and whether the non-financial data was utility or telecommunications payments. However, the records examined in the US case, even the thin file population, had much more extensive traditional financial data. As such, adding non-financial positive data is likely more impactful in the Australian and New Zealand case due to the presence of less positive traditional credit data. This was clearly seen in the US case, where the impact of utility and telecommunications data was much larger in those files with less traditional information than in the average file. Needless to say, those files with many accounts already reported were impacted very little from the inclusion of an additional account. In this sense, the inclusion of non-financial data was found to be most helpful to those traditionally underserved by mainstream financial institutions, such as members of low-income households, the young, and others new to credit.

A second important point is that the changes in model performance and acceptance rates are based on those records that have scores both with and without the telecommunications account data. In the US analysis, around 16% of records were unscoreable without the telecommunications account data. That is, these individuals did not experience a change in score; rather, they became scoreable. Similarly, approximately 22% of the sample examined here had no data (including applications) when the telecommunication account data was removed.

As such, beyond the increase in model performance and the increase in acceptance among records scoreable with and without the telecommunications data, a good number of consumers would be able to begin building the fair file credit record as telecommunications data is reported. This will become more and more important as Australia shifts to more comprehensive reporting. Since having no information on file is viewed much less favorably in a more comprehensive credit sharing environment than in a negative only environment, in which a lack of information can be viewed as a lack of derogatory information. So the reporting of non-financial account data (such as from telecommunication and utility accounts) will become ever more important in Australia and New Zealand.

The US analysis of the impact of including utility and telecommunications account data also showed that individuals most underserved by the status quo, the young, members of low income households, and ethnic minorities, benefited the most from the inclusion of non-financial account data. For instance, while the inclusion of non-financial account data increased overall acceptance by about 10% for a target default rate of 3%, it increased acceptance among ethnic minorities and the lowest income households by more than 20%. Renters (as opposed to home owners), younger consumers, and non-English speakers also saw greater than average increases in acceptance. Including non-financial account data in more comprehensive credit reporting allows consumers to build a good credit and payment record using the most common everyday payments and without going into debt.

[12] Turner et al., "Give Credit Where Credit is Due: Increasing Access to Affordable Mainstream Credit Using Alternative Data." PERC, 2006.

It should also be noted that the impact of telecommunications in this study (and in the US analysis) included timeliness of payment (account payment status) data. As discussed, these are the most information rich data elements. And to reiterate, these data elements account for most of the increase in performance from the additional fair file data. Consequently, in order to realize the full benefits of the non-financial account data found in this project and in other studies, timeliness of payment data (account payment data) should be reported on these accounts as with other types of accounts.

3.5 Socio-Demographic Impacts

Up to this point, focus has been on the total portfolio impact of the inclusion of new data elements, such as fair file data elements or telecommunications payment data. In this subsection, and to some degree the next, the distributional impacts of the inclusion of the fair file data elements are explored. As noted earlier in this report, evidence from other economies suggests that an increase in data sharing leads to fairer lending, in the sense that those who most benefit are those most underserved by the status quo.

While the data available did not include household income or race, it did include age, so results are segmented by borrower age. In Australia, as in other economies, it is the younger borrowers who have the highest reject rates (or lowest acceptance rates). It is this age group that is the most underserved by lending.

Figure 9: Change in Acceptance Rates by Age in Shift to Fair File Model

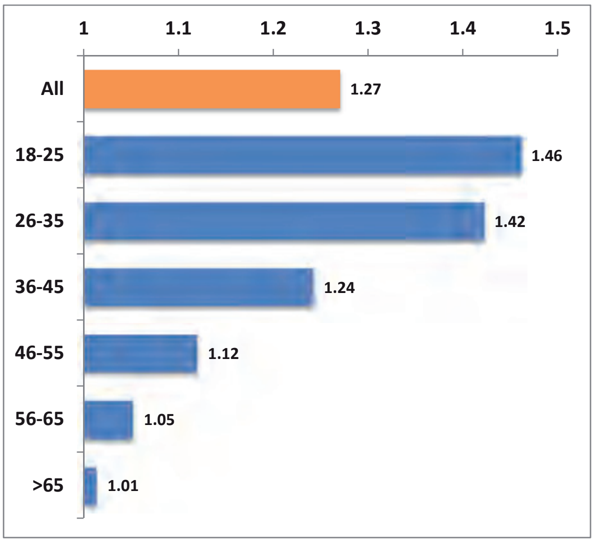


Figure 9 presents the change in acceptance rates by age group. From figure 6, earlier in the report, it was shown that total acceptance could rise from 72% of applicants to 92% of applicants with the inclusion of fair file data at a 4% target default rate. This is a rise of 27% (when using the unrounded exact figures), which is shown in figure 9 for the All category. As can be seen by the other age categories, this 27% rise is not uniform across borrower age. Younger borrowers benefit the most, with those 35 and under seeing an increase in acceptance of over 40%. The beneficial impact of the new data declines with age, with the most senior age group, those over 65, seeing only a 1% rise in acceptance. All the major age groups do, nonetheless, see some benefit from the additional data.

From a practical, economic life cycle (permanent income hypothesis) point of view, it is the young for whom unsecured credit is of most value. It is disproportionately young adults who need to borrow for homes, automobiles, and education while having the least collateral and while at the early stage of their lifetime income cycle. It is for this group that more accurate risk assessment is of the most value.

3.6 Impact on those with a Previous Bureau Derogatory

Beyond the distributional fairness of credit by socio-demographic characteristics, there is also fairness relating to past credit and payment behavior. One of the virtues of full-file systems is that they are forgiving systems. For instance, in a negative-only system, if a borrower lost his or her job, had costly health problems, legal issues, or had some other event occur that resulted in a default, then that borrower could be virtually cut off from credit for five, perhaps up to seven, years. This would essentially ignore situations in which the borrower may have found new employment after a year of unemployment and had paid all other obligations on time following the default. That is, negative only systems remember past very bad payment behavior but do not include information when the borrower's behavior changes. There is little ability to rehabilitate one's credit standing. This would make the financial recovery for those who experienced a temporary financial setback all the more difficult.

Table 3: Acceptance Rate for Those with a Previous Bureau Derogatory

	With Prior Derogatories	
Target Default Rate	Base	Fair-File
	(Negative-Only)	
2%	0%	0.5%
3%	0%	1%
4%	0%	6%
5%	0%	16%
6%	0.3%	28%

In a full-file/fair file system, the recent credit and payment behavior of borrowers is captured, which in turn allows for a credit standing rehabilitation, creating a much more forgiving credit system. This effect is exactly what is seen in the results in table 3. Those with a past bureau derogatory are much more concentrated at the bottom of the score distribution of the negative-only system than in the fair file system. Lenders with portfolios with a score cutoff consistent with a 2%, 3% or 4% target default rate would not accept any borrower with a past bureau derogatory in a negative-only system. In a fair file system, up to 6% of those with a past bureau derogatory could be accepted. The difference is even starker as one goes deeper down the distributions. A near prime or otherwise below prime portfolio might go down to a 6% target default rate, here again virtually no borrower with a past bureau derogatory would be accepted in a negative-only system, whereas over a quarter (28%) of such borrowers would in a fair file system. By way of comparison, for a 4% default target, the acceptance rate rises from 75% to 95%, with the inclusion of the fair file data elements for those records with no prior bureau derogatories. And for all records, the acceptance rate increases from 72% to 92%.

Of the 1.8 million records, 5.9% had a prior bureau derogatory. Extrapolating this rate out to the credit active population of Australia would mean that over 600,000 Australians are currently shut out of credit access due to past mistakes. If we assume that 28% of this population would gain access with the sharing of more positive data (such as through a demonstrated record of on-time payments) then this translates to over 170,000 Australians that would have gained and utilized the opportunity to rehabilitate their credit standing.

While the fair file case clearly does not open up the door to mainstream credit to the majority of those with a past derogatory, it does enable the credit system to be much more forgiving relative to the negative-only environment.

4. Conclusion

Should it fail to move pending credit reporting reform legislation forward this year, Australia will become increasingly isolated within the Asia Pacific region—where 11 countries have moved away from negative only to full-file reporting over the past eight years—and globally, where only France, Belgium and Norway maintain strictly negative only credit reporting regimes (and France has reform legislation pending).

While there has been recent success in reforming the Australian system—and the fact that New Zealand was first past the post in this regard may help—given the uncertainties associated with minority Government, and the way the issue is currently framed as being largely about "bank profits" vs. "consumer privacy protections," the reform journey is likely to continue to be incremental.

Proponents of credit reporting reform would do well to reframe the public policy debate. The credit perspective should focus on making lending smarter (less risky, fewer mistakes), more inclusive, and fairer—even more fairly priced as lenders are able to reward good credit behavior with lower prices. And while data privacy is an important value, it must be weighed against other social values, like inclusiveness, forgiveness and equity, asset building and wealth creation, and sustainable economic growth through increased lending to the private sector.

In addition, efforts should also be made to broaden the coalition of supporters to include the non-financial creditors—such as energy utilities and media firms—who will be affected by the proposed reform in Australia (and the actual reform in New Zealand). Positive steps taken through the Australasian Retail Credit Association (ARCA) and the Credit Industry Council (CIC) toward that end should be encouraged.

Finally, and on an optimistic note, proponents of further credit information sharing reform should begin preparing now for the next increment. For lenders, this may mean building additional data fields into systems upgrades to permit new data elements to be seamlessly integrated in the near or medium-term. It also means securing executive level buy-in for the resources necessary to sustain reform efforts to transition from a fair-file to a full-file regime. This includes IT, legal, government affairs, customer relations, and external communications. Without a commitment to this from the top, industry efforts will flounder and additional highly predictive data elements—including outstanding balance and payment amounts—will be left off the table.

GLOSSARY

Account Payment Status — for any credit account (financial or non-financial), information as to the present disposition of the account. For instance, whether an account is current, 30 days past due, 60 days past due, or 90 days past due.

Bads — a definition used in a credit scorecard, this is typically defined as a prospective borrower who is 90 or more days late with a credit account or has a default or other serious derogatory over an observation period.

Comprehensive Reporting — a credit information sharing system that includes payment data from banks, non-bank lenders (e.g. retailers), and often non-financial services creditors such as energy utility or telecommunications service providers. This is the antithesis of a "fragmented" system, in which credit information is siloed in specialty credit bureaus according to industry sector (bank, non-bank, credit card, non-financial services, retail, etc).

Data Furnishers — those firms that provide customer or borrower account payment information to one or more credit bureaus. Examples include a mortgage lender reporting information on a mortgage holder's account, or a telecommunications provider reporting on an account to a credit bureau.

Derogatory — in the context of a credit file, derogatory information typically refers to negative payment or account status information, including writs, liens, bankruptcies, judgments, collections, defaults, and delinquencies. In the cases of Australia and New Zealand, all account status derogatories are considered "positive" information.

DPD — an acronym for "Days Past Due," which is account payment status information. This is a descriptive metric of concern for lenders as it pertains to cash flow.

Fair File — a policy term of art in the credit reporting reform efforts in Australia and New Zealand. This refers specifically to the credit information sharing regime that took effect as of April 1, 2012 in New Zealand and the pending proposed reform in Australia. In addition to negative data, credit bureaus in New Zealand would collect additional positive data elements, such as account type, date account opened, and account payment status (whether the account is current, 30+. 60+, or 90+ days beyond term). The proposed regime in Australia will be identical, but for payment status on non-financial accounts, which will be precluded.

Full-File Reporting — this refers to a credit information sharing system that permits the sharing of negative and positive account information, including payment amounts, outstanding balances, age of debt and other variables that are excluded from a Fair File system. This is the system that is found in the U.S., the U.K., and other countries.

Goods — a definition from a credit scorecard. A "Good" refers to a prospective borrower who is considered unlikely to be 90 or more days late in meeting their debt obligation(s) over a 24-month period.

Negative Only Reporting — a credit information sharing system that permits only derogatory information to be furnished to credit bureaus. This system has been in place in New Zealand, and is currently in place in Australia. The global trend is to permit greater information sharing for purposes of financial safety and soundness, and fairness and equity in lending. Among advanced countries, only Australia, Belgium, France, and Norway maintain negative only systems.

Non-Financial Accounts — accounts in a consumer credit report that are reported by non-financial creditors. This typically refers to energy utilities and telecommunications and media service providers. Such firms are generally classified as creditors as they provide consumers a good or service in advance of payment, then issue an invoice/bill with a grace period (typically one month) for payment. This transaction effectively represents a form of credit, and yields payment information that is highly predictive of traditional credit behavior.

Thick-File — a credit report typically containing information on two or more tradelines or accounts reported either open or closed. While the exact definition differs from system to system, these are files that contain abundant information. The term Deep-File is also used to describe such files.

Thin-File — a credit report typically containing information on less than 2 tradelines or accounts reported either open or closed. While the exact definition differs from system to system, these are files that contain the least information on a borrower. The term Shallow-File is also used to describe such files.

Tradeline — account information as included in a consumer credit report. A person with only a mortgage loan, an auto loan, and three credit cards reported to a credit bureau would have five tradelines in their credit report. Tradelines sometimes refer to public record information in a credit report, including judgments, writs, liens, bankruptcies, and other data provided by government agencies. The exact definition of tradeline differs from system to system and can even differ bureau to bureau in a system.

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