A LOOK INTO TRENDED DATA

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Trended Data

Credit trended data provides an expanded, more granular view of the consumer by leveraging 24 months of a consumer's past balance, scheduled payment amount, actual payment amount, and credit utilization history. Equifax's proprietary algorithm is applied to trend these time-series data across trades and industries to capture the shape, duration, intensity, and magnitude of changes in the consumer's financial behavior. This is a deeper view of a consumer's credit behavior, supplementing the traditional static credit snapshot with a dynamic picture of a consumer's history of managing lending products.

Additionally, using the actual payment amount lets you see if the borrower paid off their balance in full each month, or if they just made the minimum required payment. One of the most powerful reasons to use trended data is that the specific payment amount carries additional information that may be helpful in predicting future borrower behavior.

While there are potentially lots of ways to use all of this information, in the data we worked with Equifax identified two groups of borrowers: *transactors*, who pay a majority of balance over a six-month window on most of their revolving accounts (which includes credit cards and home-equity lines of credit), and *revolvers*, who pay less than a majority of balance over a six-month window on most of their revolving accounts.

Connecticut Avenue Securities (CAS) Data

The Fannie Mae Connecticut Avenue Securities (CAS) program was launched in 2013 and created a new market for investing in mortgage credit risk. CAS deals are designed to share credit risk on a portion of Fannie Mae's single-family mortgage portfolio. Equifax Credit Risk Insight for CAS enhances Fannie Mae loan-level performance data with monthly updates of Equifax consumer risk scores, credit attributes, and trended data. The transactor and revolver flag used in this study came from this dataset.

Our data set consists of 19 CAS deals issued between 2013 and 2017 and performance data on these deals from April 2014 to May 2018. We restricted the sample to only those deals that have at least 12 months of performance history. All together the sample consists of over 3 million unique mortgage loans.

Analysis Methodology

In this study, we focus on understanding the value of one trended data attribute—the transactor/revolver flag in predicting mortgage delinquency in CAS deals. We take an analytical approach to show how the transactor/revolver flag could further separate risk after controlling for the information found in credit scores and in our own proprietary models. We'll also try to show the relative strength of the transactor/revolver flag compared to some of the other common binary variables used to predict mortgage delinquency.

[1] http://www.fanniemae.com/portal/media/business/credit-data-092216.html

Let's start with a few tables showing summary information about the data set.

Figure 1. Transactor/Revolver Distribution in CAS Deals

Category	Count	Pct
Revolver	1,342,607	41.6%
Transactor	863,040	26.8%
Missing	1,017,931	31.6%
Total	**3,223,578**	**100.0%**

Figure 1 shows the borrower's status as a transactor/revolver at the time of deal issuance. CAS deals are typically issued with loans that are at least 12 to 24 months seasoned, so the transactor/revolver distinction represents the borrower's behavior prior to deal issuance.

The transactor/revolver flag can be missing for a variety of different reasons. One would be if a borrower doesn't have any revolving accounts as of this date. Another possibility is that the borrower does have a revolving account, but the information needed to calculate the flag, for example, the actual payment amount, is not being reported.

Figure 2. Transactor/Revolver Distribution by Deal Name

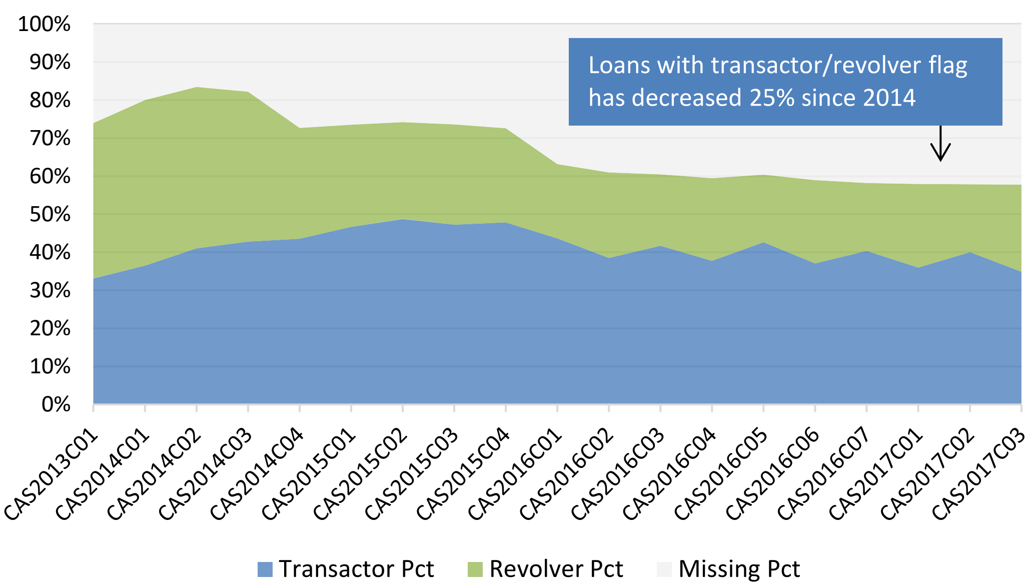


Figure 2 shows more information about the distribution of transactor/revolver/missing for each deal in the data set. The number of loans without missing information has decreased 25% off the peak in the first deals. According to Equifax, over time, major bank card issuers stopped reporting the actual payment amount data for bank cards to the credit bureaus as it became viewed as proprietary information. The low actual payment amount fill rate could result in diminished value both in underwriting decision, as well as in the predictive power of transactor/revolver flag in mortgage default and prepayment modeling.

Figure 3. 60+ Delinquency Rates (12 months after issuance)

Category	Count	Pct
Always Current	3,208,106	99.52%
Ever 60+	15,472	0.48%
Total	**3,223,578**	**100.0%**

Figure 3 shows the number of loans that had any 60+ day delinquency in the 12 months after deal issuance. Delinquency rates in CAS deals are very low in this observation window, less than 1%, which is much lower than delinquency rates observed prior to the crisis. However, because of the large size of the deals, there are still more than 15,000 examples of delinquent loans present in the data set.

The 12-month measure was chosen to make it extremely straightforward to compare deals, as they will all be analyzed during the same age window. Sixty days delinquent is a measure that we often use in delinquency analysis; missing two payments is much less noisy compared to missing a single payment, but still captures the early part of a borrower's decision.

Transactor/Revolver vs. Credit Score

The first thing we'll do is analyze whether the transactor/revolver variable has any effect beyond the credit score reported in the CAS Deals—which does not include any trended data variables in its calculation.

Figure 4. Average Credit Scores for Transactors/Revolvers

Category	Count	Pct	Credit Score
Revolver	1,342,607	41.6%	737
Transactor	863,040	26.8%	773
Missing	1,017,931	31.6%	758
Total	**3,223,578**	**100.0%**	**753**

As may be expected, Figure 4 shows that on average, transactors have better credit scores than revolvers. It's also worth noting that the average credit score for borrowers where data is missing falls in between transactors and revolvers and is close to overall average for all deals.

Figure 5. Transactor vs. Revolver Delinquencies by Credit Score

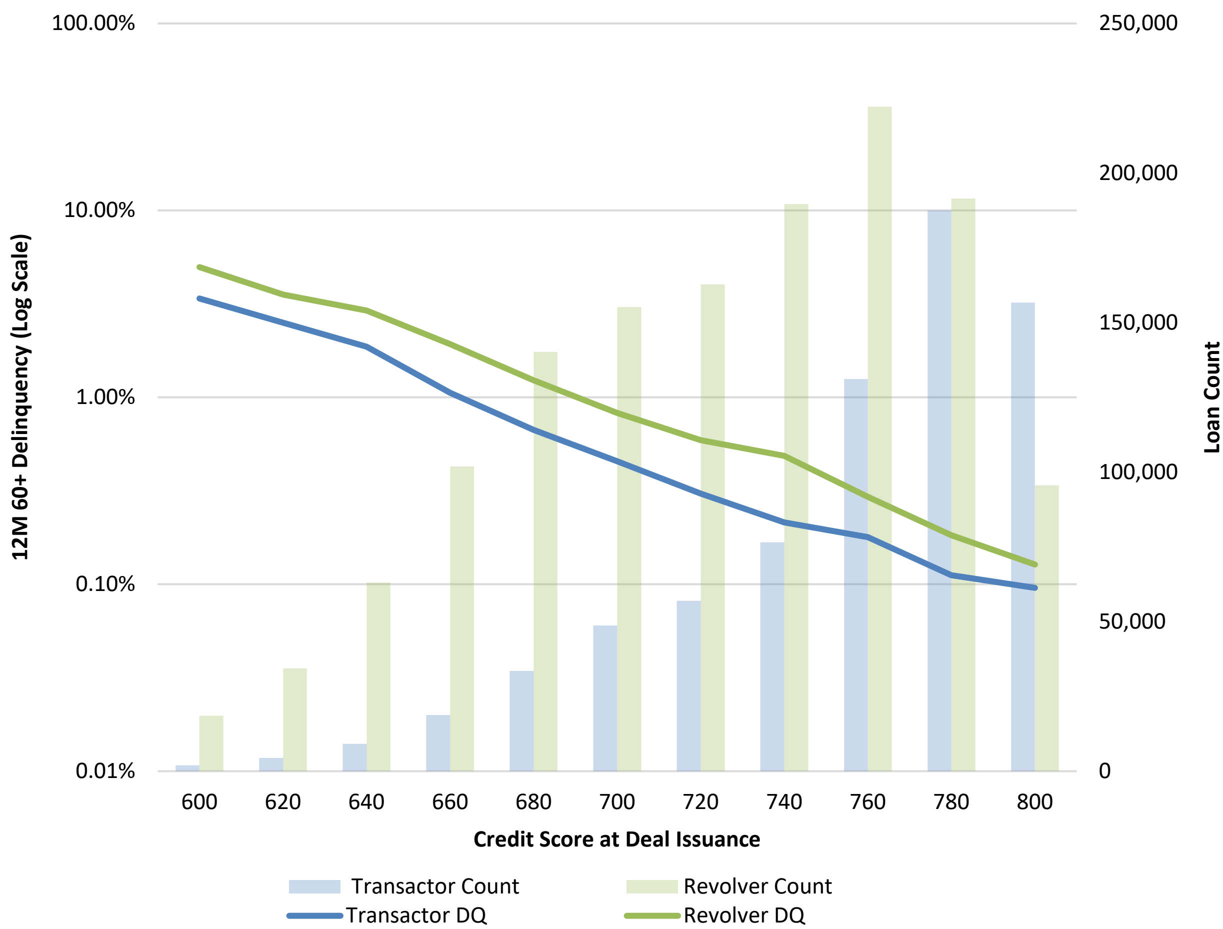


Figure 5 shows the borrowers bucketed by credit score. The shaded areas show the distribution of transactors and revolvers across each bucket. You can see that at the lower end of the credit score bucket, there are fewer borrowers in general, but also a much larger concentration of revolvers. At the higher end of the credit score bucket, there are more transactors, but still quite a few revolvers as well.

The lines represent the percentage of loans that had a 60+ delinquency across different credit score buckets. In every bucket, the revolvers have a higher delinquency rate. The average ratio2 across all the buckets comes out to 1.729, which means that within a credit score bucket, revolvers were about 1.7 times more likely to experience a delinquency, which is a good sign for the predictive power of the effect. Note that the chart is shown on a log scale: This is consistent with the way credit scores are calculated, which also use log odds.

For purposes of comparison, we evaluated this ratio against similar ratios calculated on this data set for other binary variables that can be used to predict mortgage default.

[2] Geometric mean, weighted by the number of loans in each bucket.

Figure 6. Variable Effect Strength for Common Mortgage Variables

Name	Description	Ratio
One Borrower	One Borrower	1.809
Revolver	Revolver	1.729
Cashout	Cashout Refinance	1.601
High DTI	Debt to Income > 35	1.585
Second Home	Second Home	1.338
PUD	Planned Urban Development	1.178
High LTV	Original Loan to Value > 80	1.170
Owner	Owner-Occupied	1.148
MH	Manufactured Housing	1.121
Multi-Unit	2-4 Unit Property	1.071
Investor	Investor Owned Property	1.064
Odd Loan ID[3]	Last Digit is Odd	1.022
First Time Homebuyer	First Time Homebuyer	1.012
Co-op	Co-op	0.905
Condo	Condominium	0.891
Refi	Rate Refinance	0.759

Figure 6 shows this chart. This is not a full modeling of the importance of all these variables[4], but just a means to generate a comparison of the transactor/revolver variable in relation to other variables in the dataset, once we account for the credit score. We can see that for this test, the revolver flag has a relatively strong effect.

Transactor/Revolver vs. LoanDynamics

LoanDynamics is a credit model developed by Andrew Davidson & Co to analyze conforming agency-quality loans and securities and predict prepayment, delinquencies, defaults and losses in a transition-based framework and fit to public historical GSE data5,6 that was released to support the credit risk transfer program.

We wanted to use a mortgage credit model because while credit bureaus have comprehensive data related to the borrower, they do not have access to loan specific information (like loan term, interest rate or loan-to-value ratio), or economic information like changes in interest rates and home prices. Our second test is to look at the explanatory power of the transactor/revolver effect using our model to control for all of these other variables.

LoanDynamics predicts monthly delinquencies, so we'll use a slightly difference metric than before. Instead of looking at the 60+ delinquency rate 12 months after issuance, we'll look at monthly transition rates, specifically the rate at which loans transition to 60+ days delinquent. We call this the Current to Delinquent transition rate (or CtoD).

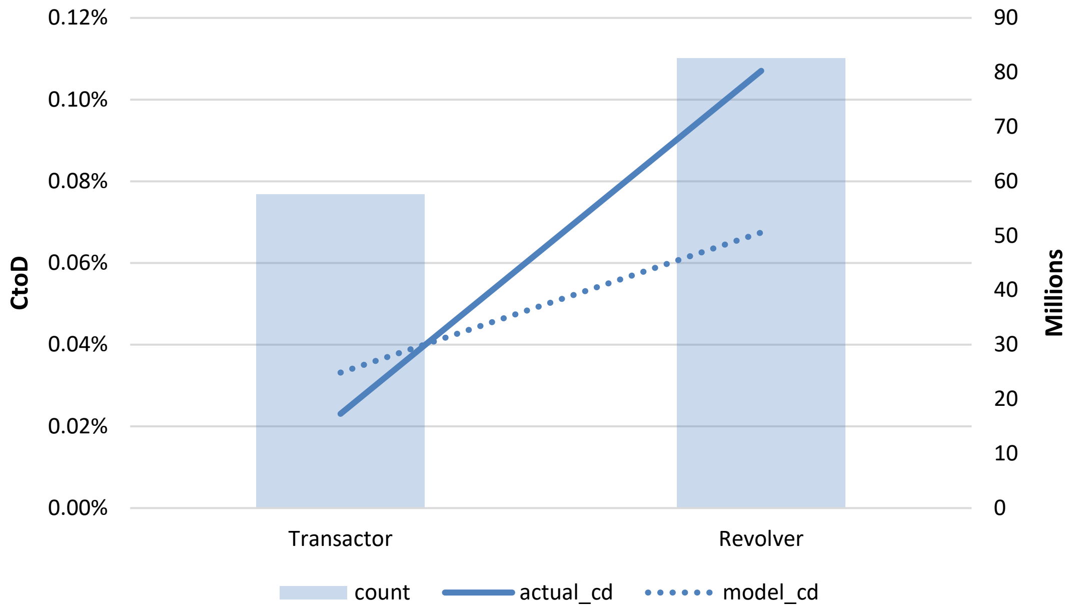
[3] This is a check against anything fishy. We would expect that loan id is going to be a poor predictive of mortgage delinquency.

[4] Note that because we are using CAS deals, we are limited to a benign post-crisis economic environment. Some variables may be more or less sensitive to economic stress; for example, a high LTV will generally matter more when home prices decline.

[5] http://www.freddiemac.com/research/datasets/sf_loanlevel_dataset.html

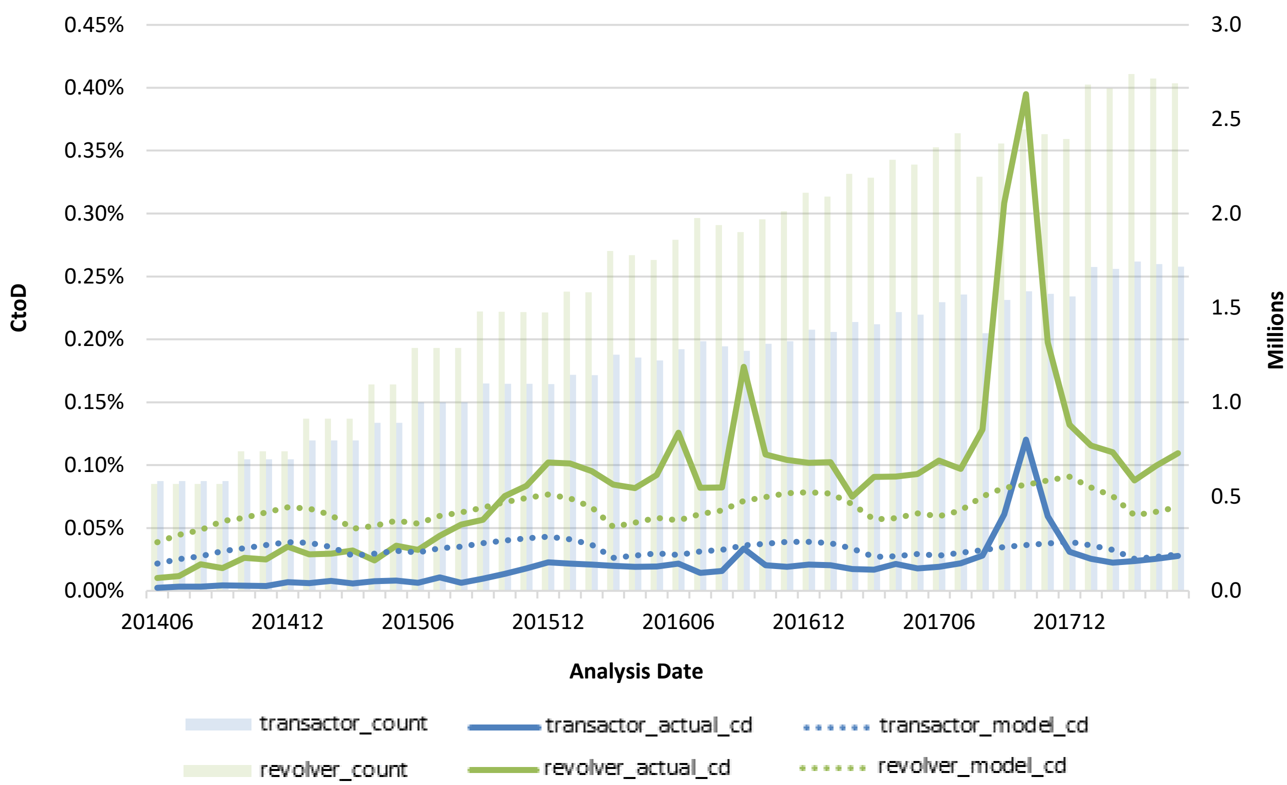
[6] http://www.fanniemae.com/portal/funding-the-market/data/loan-performance-data.html

Figure 7. 60+ Transition Rates by Transactor/Revolver



The model does predict that revolvers will have a higher delinquency than transactors based on other information. However, the modeled predicted slope (dashed line) is not as steep as the actual slope (solid line). This means that while other variables in the model have some ability to differentiate between transactors and revolvers, they don't fully explain the difference between the two. Aggregated together, transactors are over-predicted and revolvers are under-predicted. This reinforces the idea that the transactor/revolver flag encodes predictive information above and beyond the information that would already be available.

Figure 8. 60+ Transition Rates for Transactors/Revolvers by Date



We also plot the modeled and observed transactor and revolver delinquency rates over time. Looking this way, we see there is a spike in the fall of 2017. This a result of borrowers who were affected by hurricanes Harvey, Irma and Maria, which is not an effect accounted for by the model. However, the transactors are clearly separated from the revolvers throughout the entire analysis window. This is a good sign; it means the effect is persistent at least for this one type of stress. If the opposite were true and revolvers had higher delinquency rates during normal times, but not during stressful times, then it would be much harder to say they were riskier borrowers in general.

Conclusion

This is a preliminary look into the effect of credit-trended data on mortgage delinquency. Some further avenues for investigation could include a full through-the-cycle analysis, research into other types of loans, and a look at whether the effect is stronger when treated as a continuous rather than binary variable. It will also be interesting to analyze how overpayment or accelerated amortization in installment loans (mortgage, auto, and student loans) predicts mortgage default. Still even from this preliminary examination, it seems reasonable to conclude that trended data is indeed a useful predictor of mortgage delinquency. Even when we controlled for other common variables, we still saw a strong effect. This makes trended data a great candidate to add to mortgage models as it includes information that would not easily be captured otherwise. We are encouraged by these results and hope to continue our study into credit bureau data to discover more insights into borrower behavior.