The Relationship between default and economic cycle for retail portfolios across countries: identifying the drivers of economic downturn

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Abstract

In this article, we collect consumer delinquency data from several economic shocks in order to study the creation of stress test models. We leverage the Dual-time Dynamics modeling technique to better isolate macroeconomic impacts whenever vintage-level performance data is available. The stress test models follow a framework described here of focusing on consumer-centric macroeconomic variables so that the models are as robust as possible when predicting the impacts of future shocks. We consider the Mexican Peso Crisis / Tequila Effect by examining Argentina; Asian Economic Crisis by considering Thailand, Indonesia, and Singapore; the Hong Kong SARS recession; and the relative lack of recessions in recent data from Canada and Australia.

Keywords: Dual-time Dynamics, Nonlinear Dynamics, Time Series Analysis, Portfolio Forecasting, Scenario-based Forecasting, Retail Lending, Stress Testing, Macroeconomic Scenarios

1 Introduction

This article is a companion to [3] in that whereas the first article lays out the modeling approach and best practices for creating stress test models using the Dual-time Dynamics (DtD) approach, this work describes the application of that to a range of countries and historical economic crises. The motivation behind this exercise is to show how to make generally applicable models when training on specific crises. For example, the Hong Kong SARS Recession was in response to fears about a deadly disease, and yet the macroeconomic shocks created can be used as a way to measure more generically how consumers respond to difficult situations.

At the other extreme, we need to create stress test models in countries where no official recession has occurred within the range of data available at most financial institutions. We need to consider how to leverage the fluctuations in growth that do occur in order to create a useful stress test model.

1.1 Method of Analysis

In some of the cases considered, only aggregate information is available, such as the Consumer Slow Debt provided by the Argentine Central Bank and the Consumer Bankruptcies provided by the Canadian Central Bank. For such data sets, standard time series modeling techniques can be employed and these cases emphasize the selection of macroeconomic variables.

In cases where vintage-level performance data is available, we can leverage the method of Dual-time Dynamics [2] to remove the impacts of the natural maturing of the portfolio and changes in the marketing plan. DtD studies the rate of events occurring in aggregate rather than whether individual events such as default or early repayment occur at an account level. The idea is that the rate of events r, is a function of the age a of the account, the vintage orgination date, v, and the calendar time t. Thus segmentation must involve cohorts of the same vintage even if the portfolio is further segmented on other features.

With DtD, the rate r is represented as a combination of three separate functions

$$lnr(a, v, t) = f_Q(v) + f_m(a) + f_g(t) \tag{1}$$

where $f_m(a)$ is the maturation function, $f_Q(v)$ captures the quality or inherent risk of the vintage, and the impact of the calendar time t, $f_g(t)$ on the rate is called the exogeneous curve. DtD recognizes that the exogenous curve involves both internal operational effects by the lender as well as external economic effects. So the curve is first investigated by experts within the lending organization to identify effects that were caused by changes in operational policy or portfolio construction. The exogenous curve is revised to remove these effecs and only then does one attempt to fit the curve to economic factors.

The following example illustrates the potential value of this approach. The example is of a US retail portfolio where the product was launched in early 1998. The maturation curve for this product shows that peak delinquency is not reached for about two years. Therefore, several years are required for the portfolio to saturate and reach its long term delinquency level, assuming no further changes in the marketing plan. Analyzing the vintage-level performance data with DtD allows us to extract the maturation, exogenous, and vintage quality curves. In essence the exogenous curve is normalized for portfolio growth, maturing, and changes in marketing plan, clarifying the impacts of the macroe-

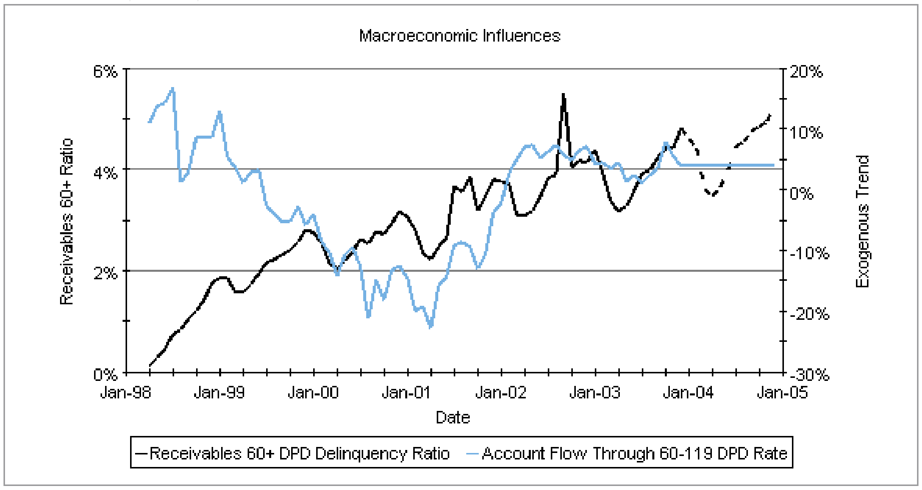


Figure 1: A comparison of the delinquency rate and corresponding exogenous curve for a portfolio launched in 1998. Note that the delinquency rate obscures the impacts of the macroeconomic environment.

The DtD method of studying exogenous curves proves to be very useful in studying economic crises in emerging markets, because the retail portfolios in those countries are also growing and maturing along with the economy.

1.1.1 Backward Extrapolation

Portfolios frequently have a small block of vintage data available and a longer historical time series of total portfolio performance. Because most emerging market portfolios are growing rapidly, the aggregate rates alone would provide misleading correlations to macroeconomic variables, because of the maturitation effect. However, the aggregate information can provide a way of solving for what the exogenous curve would have been to create the observed performance.

To extrapolate the exogenous curve backward, a set of equations is required that relates the vintage variables being analyzed with DtD to the total portfolio metrics available. When we analyzed the Thai and Indonesian portfolio data, the vintage variables were $DR(v,t)$, the flow through n months delinquent, and $AAR(v,t)$, the active accounts for vintage v at calendar time t. These two rates are defined as

$$AAR(v,t) = AA(v,t)/BA(v) \tag{2}$$

$$DR(v,t) = DA(v,t)/AA(v,t-n) \tag{3}$$

where n is the number of months delinquent, e.g. accounts that are three months delinquent would be compared to Active Accounts three months prior. BA is the Booked Accounts at the start of the vintage, and AA is Active Accounts. We define $t = 0$ at the start of the vintage data set, and that data includes vintage performance data for $t > 0$ for all vintages including those originated for $v < 0$. The goal is to extrapolate the exogenous curves backward for $t < 0$.

AAR is modeled just with a maturation function. Since $a = t - v$, this is expressed as

$$ln(AAR)'(v,t) = AAR_m(a) + \epsilon_{AAR}, \tag{4}$$

while the default rate is modelled using the full DtD model, namely

$$ln(DR(v,t))' = DR_m(a) + DR_g(t) + DR_Q(v) + \epsilon_{DR} \tag{5}$$

Note equations 4 and 5 can be solved via DtD for $DR_m(a)$ for $a \geq 0$, $DR_Q(v)$ for any v, and $DR_g(t)$ for $t > 0$.

The goal is to extrapolate the exogenous curve $DR_g(t)$ backward for $t < 0$, and this can be done by choosing the exogeneous curve that gives the result that best approximates the total number of n month delinquent accounts over the period $t < 0$ where this is available at portfolio level but not vintage level. To do this define

$$AA'(v,t) = AAR'(t) * BA(v) \tag{6}$$

$$DA'(v,t) = DR'(v,t) * AA'(v,t) \tag{7}$$

where $DR_g(t)$ for $t < 0$ is the only unknown function. Choose this function so that if

$$DA'(t) = \sum_v DA'(v,t), \tag{8}$$

then the square of difference between the estimated and observed n month delinquent accounts at each time t,

$$\eta_t = DA'(t) - DA(t), \tag{9}$$

is minimized.

Since $DR_g(t)$ is non-parametric, a simple Quasi-Newton, one-dimensional solver seeded from $DR_g(t+1)$ is used to estimate the value of $DR_g(t)$ that minimizes η_t^2. The oldest part of the exogenous curve has large uncertainty due to the diminishing number of vintages. In some cases, only annual vintages are available for that oldest section, exacerbating the error. We truncate the series when the error gets unacceptably large, but the augmentation for the series analyzed below added several years of information, allowing the seasonality and macroeconomic effects to be better distinguished.

2 Retail Credit Impacts

Experience with modeling retail portfolios in various countries has led to one key suggestion. Select variables with clear, intuitive relationships to retail lending. To make stable stress testing models, one needs to focus on what drives consumers rather than what drives the economy. Our goal is to create a model of what drives consumer behavior and rely on economists to create scenarios for those inputs from broader economic models.

Figure 2 encapsulates this consumer-centric world view. By looking for macroeconomic variables that track the inflows (solid lines) and outflows (dashed lines) of consumer wealth we hope to model the changes in consumer delinquency and default rates. The diagram considers four major categories: employment, assets, loans, and consumption.

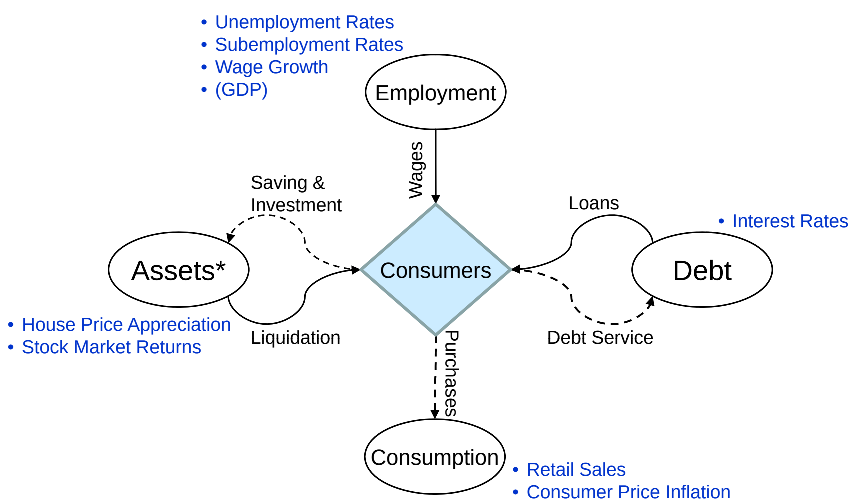


Figure 2: A simple model of the forces impacting consumer delinquency from a macroeconomic perspective.

Employment is the most obvious and generally provides the strongest macroeconomic indicators of consumer delinquency. Metrics like employment, unemployment, and sub-employment rates are usually available for economies around the world and have provided consistent correlations to delinquency and default rates across many types of economies. Measures of wage growth can also provide good indicators of consumer credit performance, but are generally more difficult to obtain.

Spending is somewhat less direct than employment. Core inflation rates can provide a measure of the stresses on consumer balance sheets and therefore can provide a leading indicator to consumer problems. Declines in consumption can also be a leading indicator of future problems, but often the lead time is too long. Although offering a long lead time seems like an advantage, many things can happen in the economy along the way, so such variables can generate unstable relationships from one cycle to the next.

Changes in asset values can have significant impacts on consumers, but are less frequent. Stock market bubbles can create a wealth effect that drives down defaults for those investing in the market. The bursting of such bubbles typically has an equally dramatic negative impact. Mortgage bubbles create similar stresses. Although these effects are significant, most countries will have only one just event within their data. Such bubbles are infrequent, so a recent mortgage bubble might provide excellent correlations, but the next such bubble is unlikely to occur for many years. The best opportunity to benefit from asset bubble modeling is to borrow experiences from similar economies and approximate what could happen in economies that have not yet experienced them.

The other asset value effect to consider is the deterioration of collateral value in support of a loan, such as mortgages and auto loans. Although not a dominant effect, anecdotal evidence shows that when a consumer takes out a loan on a house or auto and later the value of that asset plunges, the consumer may elect to "send in the keys" rather than continue to make payments. One classic example is with wrecked cars. When a vehicle is totaled, the consumer can be indignant upon being informed that they are still liable for the outstanding balance of the loan.

These are not financially rational decisions, because of the damage done to the consumer's credit record, their diminished access to future loans, and the interest rates assessed on other outstanding loans and lines-of-credit. Still, many of the aspects we are modeling in this paper are behavioral rather than financial in origin.

The fourth consumer driver is outstanding consumer debt. When interest rates fall, consumers can often refinance their debt, creating more cash flow. Rises in interest rates can be equally damaging as adjustable rate products require higher servicing payments. Debt burden is a commonly considered metric. Generally speaking, debt burden has been rising for consumers globally for decades. Gradual increases seem to reflect changes in lifestyle and attitude toward credit. Certainly, higher debt burdens make consumers more sensitive to economic shocks, but gradual rises in themselves do not appear to be the root cause of delinquency shocks. However, sudden rises in debt burden, such as those due to interest rate shocks, can definitely trigger consumer delinquency events.

How consumers manage their debt is also strongly dependent on the laws in place. Changes in bankruptcy laws, minimum payment rules, and interest rate caps all have strong impacts on consumer behavior. Although not strictly macroeconomic, these effects can be dramatic. Unfortunately, regulatory events tend to be one-time shocks that can be modeled retrospectively, but can only be anticipated approximately by studying other economies where such events occurred.

Death, divorce, and serious medical problems are not included in this diagram. All of these impacts are known to be important drivers of individual consumers defaulting on their credit, but they are problematic when used for stress testing. At least in the US, divorce and medical records are not allowed when building account-level models. Technically, they can be used for making portfolio-level, strategic decisions, but portfolio managers refuse to consider such variables, because of the reputation risk given the likely misunderstanding by the public regarding how they are used. Also, macroeconomic variables often correlate to these effects. For example, financial stress is the leading cause of divorce in the US [4]. Similarly, medical problems do not cause loan delinquency, however the corresponding costs of those medical problems drive delinquency, and macroeconomic variables will usually capture issues such as spiraling medical costs. A war or epidemic could, of course, cause the direct death of loan holders, but those situations quickly lead to systemic failures of the financial systems in a country. To some extent, those events are also captured in macroeconomic factors, if such metrics are still being recorded under such extreme circumstances. In stress testing, we are not trying to capture every factor that may cause a consumer to go delinquent. Rather, we are trying to identify factors that may correlate well to changes in the baseline level of delinquency and are consistently available across economies.

In the following sections, we will provide examples for many of these relationships by looking at historical data for different economies.

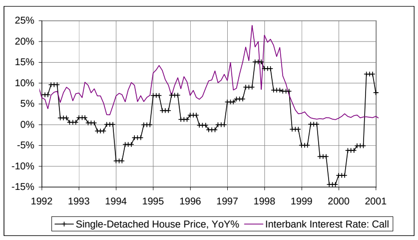
3 Thailand 1997 Asian Economic Crisis

The Asian Economic Crisis in 1997 provides a powerful case study. Researchers have offered a range of opinions on the root causes of the crisis [8, 5, 11]. Overall, it seems clear that investors were becoming concerned about pressures building within the economy, which precipitated outflows of investment funds from several economies.

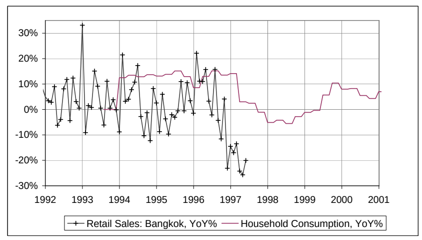
From the perspective of Thai financial centers, the crisis began in early 1997 with a run on the Thai currency. The shock in current account deficit precipitated first an interest rate change and then floating the Baht against other currencies. Within the country, and particularly Bangkok, the end of the foreign investment influx caused a crash in the overbuilt commercial real estate market and led to the government's closure of 56 distressed financial institutions in December of 1997. As construction and other industries suffered from a liquidity crunch, consumers lost their jobs. The inevitable result was a rise in unemployment and a rise in loan delinquencies.

From a consumer perspective, the onset of the crisis can be seen earlier. At the beginning of 1996 the changes began. House price appreciation slowed dramatically. At the same time, retail sales started to slide and unemployment began to tick up. This was not a recession, but the early indication that the economy had begun to overheat. Over the next year this appeared to create the imbalances that led to the run on the Baht and economic crash.

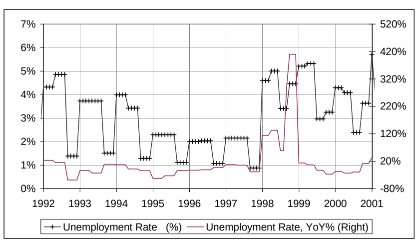
From this period, the authors were allowed access to vintage-level data from



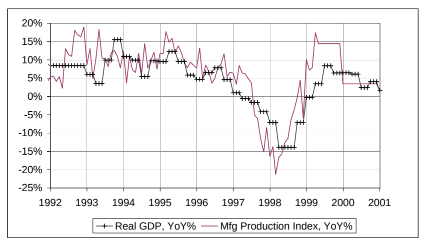
(a) House price data is compiled from the Government Housing Bank (GHB) and available from the Bank of Thailand. Interest rates are from the IMF - IFS database.



(b) Data from the IMF - IFS database.



(c) Data provided by the National Statistical Office in Thailand.



(d) Data from the IMF - IFS database.

Figure 3: Comparison of Thai macroeconomic data during the 1997 Asian Economic Crisis. YoY% refers to a computing the ratio of a given month to the same month in the previous year and expressing the result as a percentage change.

some retail loan portfolios in Thailand. The vintages were originated from 1990 through September 1998. The vintage performance data covers a period from February 1995 through September 1998. This data was processed with DtD to extract maturation, exogenous, and vintage quality curves. Because of privacy concerns, only the exogenous curves capturing the environmental impacts are shown here.

In addition, the authors also had access for some portfolios to aggregate data going back as far as April 1990. The aggregate data was analyzed with the backward extrapolation method described earlier to estimate what the exogenous curve would have been in order for the total portfolio to behave as observed.

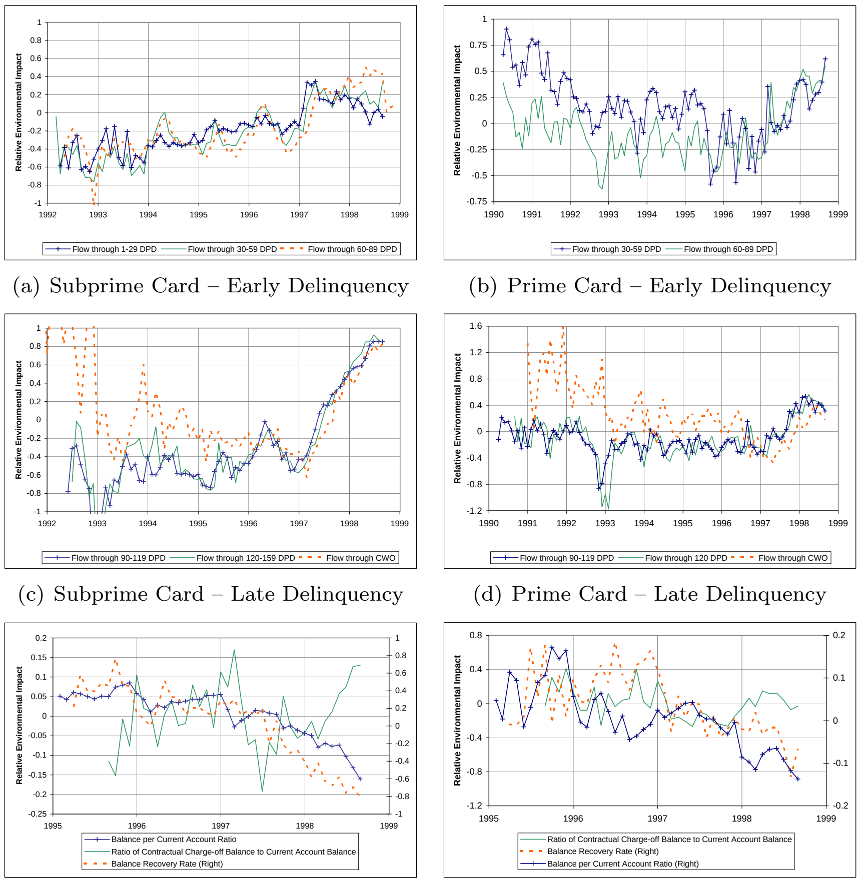
This analysis was applied to data for prime and subprime credit card portfolios in Thailand. These portfolios had experienced strong recent growth and significant changes in originations policies. The DtD decomposition isolated and removed those effects. With the completion of this process, we have the exogenous curves for delinquency and balance dynamics extracted for vintage data from early 2005 through mid 2008. Using the aggregate information, we extrapolated the delinquency exogenous curves back through 1992, though with higher noise for the oldest parts.

Studying first the Subprime Card, bucket one delinquency was rising steadily but gradually for several years preceding the 1997 shock. This period could be explained by growth in credit lines during this period or a number of other policy changes. The next two delinquency buckets improved in 1995 relative to 1994, but began to deteriorate in 1996. The dramatic rise in early 1997 coincides with the economic collapse. However, some of that early 1997 rise appears to be the usual seasonal delinquency when compared to previous years. The apparent recovery in the first two delinquency buckets in mid 1997 is thus likely just transitory. Real improvement in early delinquency does not begin until 1998. Looking to the late delinquency stages, we see that improvements never come within the available data.

Overall we see that a large burst of delinquency occurred immediately. One year after the onset of the crisis, accounts may not be going to one-month-delinquent any more frequently than before the crisis, but those accounts will go seriously delinquent at a much higher rate than previous years. When considering Basel II stress testing, the Flow through 90-119 DPD is a good proxy for the probability of default (PD) rates.

The exogenous curves for the balance dynamics were limited to just the results from the vintage analysis. Balance per current account was relatively flat, with seasonal variations, to the beginning of 1997. At that point, management likely began to rapidly curtail the available credit lines.

The Ratio of Contractual Charge-off Balance to Current Account Balance showed a dramatic spike at the beginning of 1997 as the crisis began. This is the usual pattern where the high balance, high risk accounts are most vulnerable to macroeconomic shocks and preferentially roll to charge-off. After those accounts, the next wave would have been large numbers of the lowest credit quality accounts that would have been assigned lower balances. These would have been



(a) Subprime Card – Early Delinquency

(b) Prime Card – Early Delinquency

(c) Subprime Card – Late Delinquency

(d) Prime Card – Late Delinquency

(e) Subprime Card – Balance Dynamics

(f) Prime Card – Balance Dynamics

Figure 4: Delinquency and Balance Dynamics for Thai Prime and Subprime Card portfolios. Relative Environmental Impact refers to how much more or less of the given metric was experienced in a given month as due to environmental changes. The axis scale is the log of the multiplicative impact with the zero line representing the overall average level observed for the data set. To convert the axis to a percentage, one would compute $e^y - 1$.

low income consumers who were generally responsible with their credit use, but were nonetheless driven into delinquency by the crisis. In the last phase, better quality accounts would be left, but as the crisis persisted, those would eventually go delinquent as well. Other explanations are of course possible for the movements in this curve. This explanation is based upon personal experiences with this and similar crises, but is essentially an hypothesis.

The combination of Balance per Current Account and the Ratio of Balance per Contractual Charge-off Account to Current Account Balance provide some insight on how Exposure at Default (EAD) would have behaved.

Lastly we have the Balance Recovery Rate. Again, this was relatively stable prior to the crisis, but plunged steadily through the recession. This is the bad news for estimates of Loss Given Default (LGD), because it shows that when PD was high, EAD was still severe, and LGD was severely worsening to the point of almost no recoveries.

For the prime credit card portfolio, the bucket data was unreliable, but the subsequent buckets all showed improvement or stability up to the onset of the shock in 1997. Unlike the subprime portfolio, however, there was no initial burst of delinquency. Prime accounts would have had more assets and presumably more reliable employment. As a result, prime delinquency rose more slowly. The bad news is that no recovery was seen through to the end of the data. At that point, the recession was severe and everyone was affected.

The balance dynamics are interesting in comparison to subprime. Current balances actually rose some at the onset of the crisis, probably because management was reluctant to cut credit lines for these consumers initially. Charge-off balance ratios fell initially, as the poorer of the prime accounts probably had lower lines and rolled through to charge-off preferentially at the beginning of the crisis. Into 1998, charge-off balances rose dramatically just as was seen in subprime, as the better accounts in the portfolio with higher lines were also pushed into default. Also as with subprime, recovery rates plunged throughout the crisis. However, noting the scale, the recovery rates did not fall as dramatically as with subprime, presumably because the prime consumers had more underlying assets.

3.1 Thai Econometric Modeling

The preceding analysis is in preparation for making an econometric model of the exogenous curve. Multi-factor models were tried, but generally produced lower F-test values than the single-factor models. Clearly, any of these primary macroeconomic variables can explain the rise in consumer delinquency. Without more training data, the best approach would appear to be to create a set of independent, single-factor models and then use a voting methodology to reduce noise and increase robustness out of sample.

The following table has the factors that correlated well to the exogenous curve for Account Flow through 90-119 DPD Rate. That rate was selected as a close approximation to the Basel II definition of default. A positive lag means that the macroeconomic factor is a leading indicator of portfolio performance.

Negative lags indicate lagging indicators, which is common for unemployment rates. The lags shown represent the maximum correlation between the exogenous curve and the macroeconomic variable being considered. A simple scan from large positive to large negative lags was performed to find the best correlation.

	ρ	σ_ρ	Intercept	B	σ_B	t-Test
Log Baht/$ Exchange Rate	0.51	0.09	-5.64	3.84	0.66	5.84
Interbank Interest Rate: Call (Lag 5)	0.63	0.09	-0.58	6.95	1.00	6.94
Log Interbank Interest Rate: Call (Lag 5)	0.55	0.09	1.49	0.63	0.10	6.43
Yield Curve Slope (Lag 6)	0.68	0.08	-1.58	0.23	0.03	8.86
CPI, YoY% (Lag 1)	0.67	0.08	-1.10	15.90	1.80	8.83
Real M1, YoY% (Lag 5)	-0.75	0.07	0.17	-5.67	0.53	-10.79
Real GDP, YoY% (Lag 11)	-0.63	0.09	-0.39	-1.57	0.23	-6.92
Mfg Production Index, YoY% (Lag 4)	-0.67	0.08	0.12	-4.50	0.54	-8.38
Imports - Consumer Goods as % GDP (Lag 3)	-0.40	0.10	1.42	-43.55	10.87	-4.01
Unemployment Rate SA (Lag -7)	0.52	0.09	-0.78	21.92	3.65	6.00
Unemployment Rate, YoY% (Lag -3)	0.63	0.09	-0.19	0.51	0.07	6.95
Single-Detached House Price, YoY% (Lag 5)	0.63	0.09	-0.30	5.23	0.76	6.91

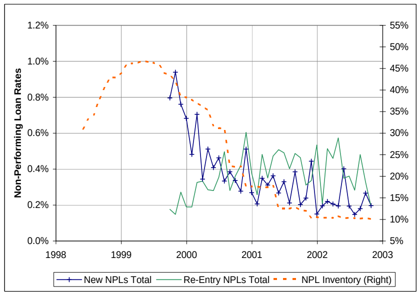
Table 1: Factors correlated to Flow through 90-119 DPD Rate for Thai Subprime Card.

The factors shown in Table 1 were chosen to illustrate a few points. Factors like exchange rates, money supply, manufacturing production index, and imports are typically very difficult to obtain scenarios. Some factors, like exchange rates, are closely tied to the details of this crisis and would not be expected to generalize well to future crises. For this reason, we focus on interest rates, GDP, unemployment, and house prices.

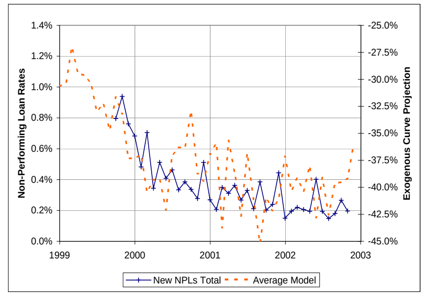
Another common question is how best to transform these variables. Interest rates are shown directly and with a log transform. In this case, the log transform lessens the correlation, but not greatly compared to the uncertainties. As a rule, a log transform may make the model more stable to simulating extreme events, as is demonstrated for the Indonesian analysis below. Unemployment rate is shown both as the seasonally adjusted rate and a Year-over-Year percentage change. Again, it is difficult to conclude which is better in general. Some practitioners make the case that change in employment is better than the unemployment rate, but that metric was not available for comparison.

Insufficient data was available to conduct an out-of-sample test. However, the Thai government began collecting statistics on non-performing loans (NPLs) shortly after the crisis [16]. From this data, we extracted the New NPLs, Reentry NPLs (previously delinquent accounts that have returned to delinquency after an initial loan rewrite), and NPL inventory. NPL is defined at accounts that are three or more months delinquenct.

The plot at left shows the three NPL measures. The plot at right compares New plus Re-entry NPLs to the average forecast from the bottom three models in Table 1. The House Price model was excluded because the post-crisis House Price data was so noisy that it would clearly not produce a reasonable forecast. Note that the forecast was made for a credit card portfolio where maturation



(a)



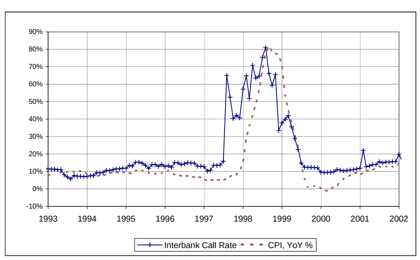
(b)

Figure 5: Non-performing loan rates provided by the Bank of Thailand.

and quality effects were cleaned out. The non-performing loans will include all products, and thus spread over time because of the varying default timing among products. Nevertheless, the model has a correlation to the NPL data of $\rho = 0.42$. If we consider that the credit card model could be a leading indicator of other products and allow for a lag, we see that at lag 2, $\rho = 0.53$ and with lag 6, $\rho = 0.80$.

4 Indonesia 1996 Stress

When the crisis began in Thailand, Indonesia seemed to be in a relatively strong financial position. Nevertheless, contagion effects caused a similar run on the Indonesian Rupiah. The final result was that Indonesia was hit hardest by the Asian Economic Crisis of 1997-1998. Adding to the instability was the ouster of the old regime in 1998. Although replaced with a more democratic government, Indonesia was hard-hit by the shock. [15]

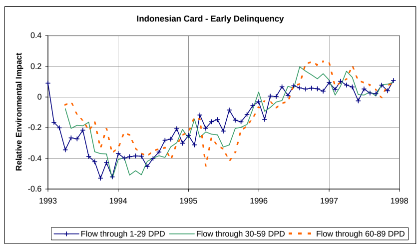


(a) Interest rate and inflation from the IMF - IFS database

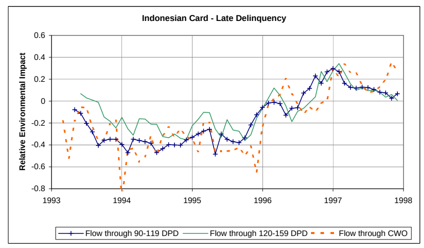
(b) Gross Domestic Product from the IMF - IFS database and Unemployment from BPS Statistics Indonesia.

Figure 6: Data for the Indonesian economic environment.

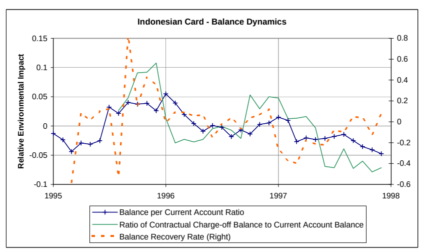
For Indonesia, we analyzed vintage-level data from a prime credit card portfolio and extracted the exogenous curve from 1995 through 1998. We also had access to previous portfolio-level performance data which we used to extend the history of macroeconomic impacts on the portfolio back to 1993 for the delinquency measures. Unfortunately, the available data ends just as the 1998 recession was beginning to be felt by consumers. However, we do capture some interesting dynamics just prior to the recession. From a consumer delinquency perspective, early 1994 market a turning point from improving in 1993 to worsening through 1996. By early 1997 consumer delinquency had begun to improve again, just before the Asian Economic Crisis hit. This pattern is also hinted at in data shown in Goeltom (2006) [6].



(a) Early Delinquency



(b) Late Delinquency



(c) Balance Dynamics

Figure 7: Exogenous curves from the analysis of vintage performance data for an Indonesian credit card portfolio.

Although the 1997-1998 shock dominates the plots of the macroeconomic data, the trends from 1994 through 1996 were clearly significant. Unemployment and interest rates both doubled through this period. There was no recession in this period in terms of GDP, but GDP began to slow in 1996 before accelerating in 1997, when it finally lifted consumers. Thus, the economy expanded overall from 1993 through 1997, but the growth was not broad based and coincided with a worsening environment for consumers. This was possible because the economic expansion was fueled by exports more than domestic consumer expenditures. This is an example where GDP growth is not a sufficient metric for the health of the consumer balance sheet, and it highlights the fact that sufficient structure can exist for retail stress testing even in environments that do not show recessions.

Interestingly, the dynamics of consumer balances of 1995 through 1997 mirror those in Thailand in 1997 to 1998 as the economic crisis developed there.

In 1995, the Balance per Current Account peaks as the consumer deterioration persists. Charge-off balances peak at this time as well, as the highest balance consumers default first. Recoveries peak early along with the high balance accounts, but then fall until the consumer recovery begins in 1997. None of the charge-offs or recoveries from the Asian Economic Crisis appear in the time period considered, so one is left to assume that this pattern will begin to repeat in 1998.

Using the Flow through 90-119 DPD Rate again as a reasonable proxy for the default rate, we considered correlations between that exogenous curve and the available macroeconomic variables. As is already apparent, economic stresses existed which come through in interest rates, unemployment, and consumer spending. However, GDP exhibited no significant relationship to delinquency and thus was left out. Unlike in the US consumer-driven economy, a disconnect between GDP and consumer health is common in developing countries where consumers may not drive economic growth. As before, multi-factor models were not statistically viable given the limited data.

	ρ	σ_ρ	Intercept	B	σ_B	t-Test
Log Interbank Call Rate (Lag 11)	0.72	0.09	1.4	1.63	0.21	7.87
Unemployment Rate (Lag 6)	0.35	0.12	-0.52	9.52	3.32	2.87
Real Consumer Spending, YoY % (Lag 4)	-0.54	0.11	0.072	-1.78	0.36	-4.90

Table 2: Factors correlated to Flow through 90-119 DPD Rate for Indonesian Subprime Card.

We have no data with which to conduct an out of sample validation. Although we get some reasonable correlations, the data quality is such that these may not be good enough forecast models. In particular, annual data is insufficient to measure the lag of portfolio impacts – the exception being that the interest rate data is available monthly up to the present time. Using just that variable to forecast, we obtain the result in Figure 8. From this, we can see that a model built on the non-recession event in 1996 does provide a plausible extrapolation for the 1998 crisis.

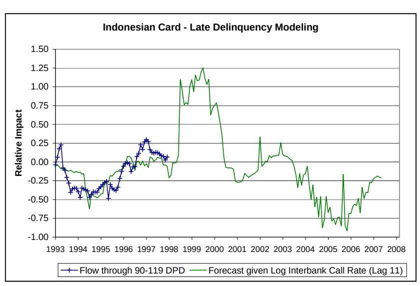
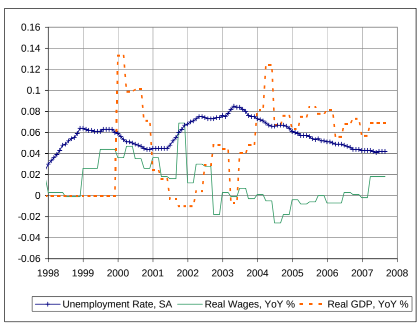


Figure 8: In-sample fit an forecast of Indonesian Card late delinquency using the log of the interest rate with lag of 11 months.

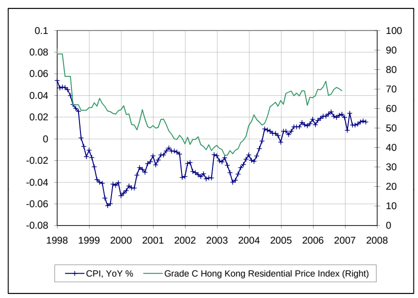
The most encouraging aspect is that the variables, lags, and correlations all make sense relative to the other results shown here.

5 Hong Kong 2003 SARS Recession

Hong Kong is unique among countries for which we have reliable macroeconomic data and mature retail loan portfolios. The data in figure 9(a) clearly shows the impacts of the Asian Economic Crisis in 1998 and the global recession of 2001.[17] However, data from 2003 shows a short recession caused by SARS, Severe Acute Respiratory Syndrome.[12] This is the only example we have of a recession caused by contagious disease. Although only 1,755 people became ill and 299 died out of a population of 6.8 million, the economy of Hong Kong took a measurable hit. Besides the short, sharp drop in GDP, we also see a "second hump" in unemployment in 2003 just when employment had started to recover following the 2001 recession.



(a) Data from the Hong Kong Monetary Authority.

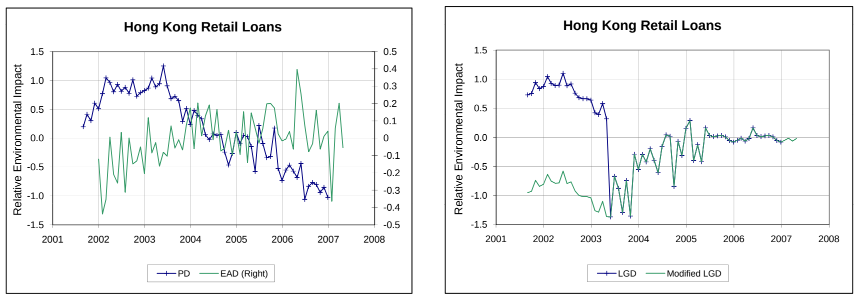


(b) CPI data from the Hong Kong Monetary Authority. House price data from the Rating and Valuation Department, The Government of Hong Kong Special Administrative Region.

Figure 9: Hong Kong macroeconomic factors related to retail lending. The Asian Economic Crisis (1998), the global economic crisis of 2001, and the SARS recession (2002) are all visible in the data and had clear impacts on retail portfolios in the area.

The significance of this event is that we can see how sensitive the economy was to the fear of an epidemic, in part through the economically dampening effects of the disease prevention measures. Since the outbreak of SARS and later Avian Flu, contagious disease is being considered more often as a potential stress test scenario. Nowhere else do we have data for the impact of disease on retail loan portfolios, but from the Hong Kong experience we see that stress test models are still possible. By correlating retail loan performance to unemployment and housing prices, we can again prepare models for the possibility of future disease outbreaks.

This has the effect of transferring the modeling challenge to economists and epidemiologists to predict the impact of a pandemic on the economy – not an easy task. Still, that is a more appropriate process than expecting a credit risk analyst to assess the impact of global pandemic directly on a bank's loan portfolio.



(a) PD and EAD

(b) LGD

Figure 10: Exogenous curves from DtD analysis of vintage performance data for a Hong Kong retail loan portfolio.

We analyzed vintage performance data from September 2001 through June 2007 for a Hong Kong retail loan portfolio, extracting exogenous curves for PD, EAD, and LGD as shown in Figure 10(b). PD shows a peak in 2002 from the 2001 global recession and again in 2003 from the SARS epidemic.

For comparison, Kang and Ma (2007)[7] show impaired card asset rates. Their data is only card, whereas the portfolio dataset analyzed here is a blend of products retail products including card, mortgage, and personal loans. More importantly, the industry wide data impairment rate is the ratio of current impaired loans to the total outstanding loan balance. Such ratios suffer from the problems of growing loan volumes, lags between origination and default, and changes in origination policy. These difficulties are the reason their data will look different from the exogenous curve in Figure 10(a) and also provide an example of how the DtD approach adds value in clarifying macroeconomic impacts on portfolio performance.

The following tables show variables that correlate well to PD and EAD. The PD correlations are in line with what we have observed previously and easily capture both recessions within the training data. Hong Kong is one of the few economies where good house price data is available, so we were also able to show that correlation. Tse (1996) [13] provides a detailed analysis of the Hong Kong housing market and house price dynamics.

The correlations for EAD are probably less reliable than PD, because there is less structure in this data. The rise in EAD after the recessions correlates to housing prices, which makes sense intuitively, but must be viewed as having limited statistical significance given that we have not seen a full cycle for this variable. Capturing a future fall in house prices would be very valuable for confirmation.

	ρ	σ_ρ	Intercept	B	σ_B	t-Test
Real GDP, YoY % (Lag 9)	-0.58	0.10	0.74	-12.38	2.03	-6.10
CPI, YoY % (Lag 3)	-0.76	0.07	-0.21	-27.39	2.58	-10.64
Grade C Hong Kong Residential Price Index (Lag 1)	-0.83	0.06	3.22	-0.0589	0.0043	-13.71
Unemployment Rate, SA, (Lag -2)	0.83	0.06	-2.89	49.79	3.50	14.24

Table 3: Factors correlated to the default rate for a Hong Kong retail portfolio, all products.

	ρ	σ_ρ	Intercept	B	σ_B	t-Test
Real GDP, YoY %	0.53	0.11	-0.16	2.63	0.53	5.00
Grade C Hong Kong Residential Price Index (Lag -13)	0.67	0.11	-0.52	0.0085	0.0014	6.04

Table 4: Factors correlated to exposure at default for a Hong Kong retail portfolio, all products.

Loss Given Default (LGD) shows an unexpected and dramatic drop in June 2003 in Figure 10(b). Changes driven by macroeconomic changes do not usually have this appearance, as is evident from the other portfolios analyzed here. As is often the case, no explanation was available from those providing the data, so we have no way of determining *a priori* whether this event is from business policy changes or macroeconomic impacts.

Given the likelihood that the June 2003 event is artificial, we modeled LGD directly with macroeconomic data and again after modifying the curve to remove the shock. Both sets of correlations are shown below. We can explain the LGD directly with macroeconomic data, but we find better macroeconomic correlations for the modified curve.

	ρ	σ_ρ	Intercept	B	σ_B	t-Test
Real Wages (Lag 8)	0.66	0.09	-0.023	18.55	2.56	7.24
Real GDP, YoY % (Lag 2) -0.41	0.11	0.41	-6.66	1.82	-3.66	
Grade C Hong Kong Residential Price Index (Lag 2)	-0.14	0.12	0.44	-0.0067	0.0059	-1.14
CPI, YoY % -0.21	0.12	0.04	-5.78	3.29	-1.75	

Table 5: Factors correlated to loss given default for a Hong Kong retail portfolio, all products.

This example highlights one of the greatest values of the DtD approach. Armed with these results, we can review with management and motivate further investigation of the shock in June 2003. This avoids simply explaining such events with macroeconomic data when deeper explanations may exist.

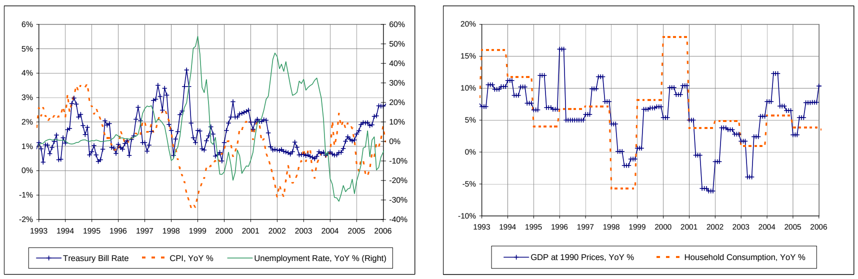
6 Singapore 2001 Recession

Singapore was lightly hit by the Asian Economic Crisis, relatively speaking. From the perspective of GDP growth and Unemployment, the 2001 global recession was much more severe [9]. Nevertheless, the Asian Economic Crisis would appear to provide ample data for creating a stress test model.

Our available retail loan data for Singapore was quite short, too short to

	ρ	σ_ρ	Intercept	B	σ_B	t-Test
Real Wages (Lag 8)	-0.52	0.10	-0.37	-12.01	2.41	-4.98
Real GDP, YoY % (Lag 2)	0.63	0.09	-0.87	8.52	1.27	6.70
Grade C Hong Kong Residential Price Index (Lag 2)	0.86	0.06	-2.26	0.0334	0.0024	13.69
CPI, YoY %	0.82	0.07	-0.34	18.58	1.61	11.57

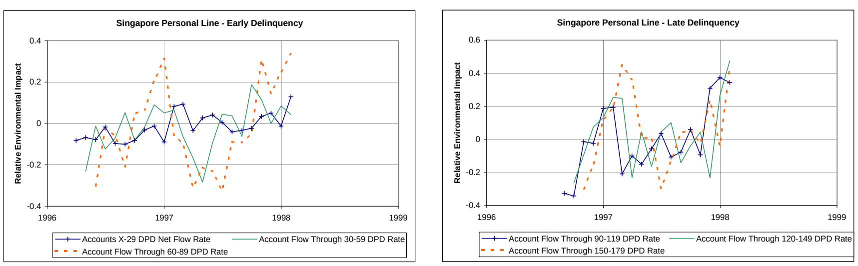
Table 6: Factors correlated to loss given default, adjusted for a possible management action, for a Hong Kong retail portfolio, all products.



(a) Data from the IMF - IFS database. (b) Data from the IMF - IFS database.

Figure 11: Data on the Singaporean economic environment.

clearly distinguish seasonality.



(a) Early Delinquency (b) Late Delinquency

Figure 12: Exogenous curves from the analysis of available Singaporean vintage data leading up to the Asian Economic Crisis.

Fortunately, there is data available on personal bankruptcies in Singapore starting in 2001. This does not allow us to analyze the Asian Economic Crisis of 1997, but we can examine this in the context of the 2001 global recession.

The Singaporean bankruptcy data, and the examples that follow, are not vintage level performance data. As such, we cannot apply DtD and instead use normal time series methods. The disadvantage is clear when the Argentine slow debt is considered later.

Correlating bankruptcy to the usual macroeconomic variables, we found reasonable correlations to the variablesin Table 7. In this case, the lags are all negative, indicating that personal bankruptcy is a leading indicator of the ma-

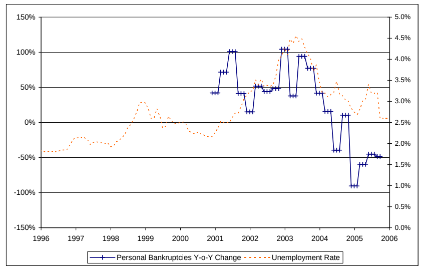


Figure 13: Singaporean bankruptcy rate data from the Singapore Ministry of Law.

jor macroeconomic indices. This is not too surprising, since bankruptcy is an accelerated path to default that can occur quicker than the contractual path to default. As we found before, multi-factor models are not statistically significant given the available data.

	ρ	σ_ρ	Intercept	B	σ_B	t-Test
PPI / WPI, Y-o-Y % (Lag -3)	-0.78	0.082	0.51	-7.61	0.80	-9.53
Real GDP, YoY % (Lag -3)	-0.64	0.10	0.52	-8.04	1.29	-6.22
Unemployment Rate (Lag -8)	0.53	0.11	-1.45	51.65	10.82	4.77

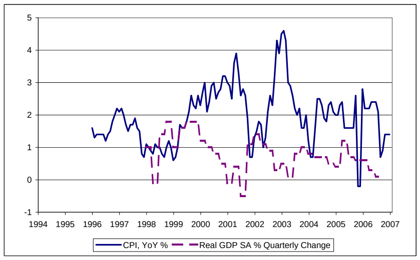
Table 7: Factors correlated to the Singaporean bankruptcy rate.

6.1 Canada 2001 Non-Recession

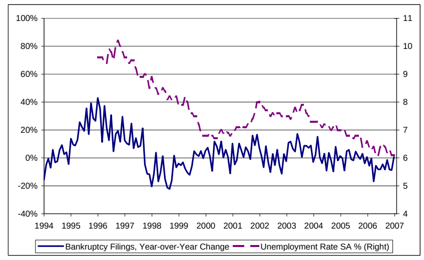
Canada is often described as a challenging environment for stress testing, because no official recessions have occured since 1990. Canada and Australia slowed but did not fall into recession during the 2001-2003 period in which the US and Europe fell into recession. However, the lack of a recession does not mean that there is no structure available for modeling.

Since aggregate bankruptcy data is available in Canada [10], we consider that as a proxy for overall consumer delinquency. Bankruptcy rates have shown long term increases, which others have studied. [1] For stress testing, we are most interested in the shorter-term oscillations that would seem visually to correlate to changes in the economy. In figure 14(a) we compare year-over-year changes in bankruptcies to several macroeconomic variables. The bankruptcy rate shown here is the number of bankruptcy filings approved in a given month. It is not an inventory measure, but it can be significantly lagged relative to economic shocks that might have caused the initial filing. Because no vintage level performance data is available, only simple time series methods were used.

Figure 14(b) shows a comparison of bankruptcy versus the unemployment rate. Although changes in bankruptcy exhibit a good correlation to unemployment of $\rho = 0.43$, there is also an obvious outlier period. In 1997 the Canadian bankruptcy laws were revised to encourage consumers to use other means of



(a) Data from the Bank of Canada.



(b) Unemployment data from the Bank of Canada. Bankruptcy data from the Office of the Superintendant of Bankruptcy Canada

Figure 14: Comparisons of consumer bankruptcy rates to Canadian macroeconomic data.

debt resolution and to defer bankruptcy filings for student loans. The effect was a significantly depressed period of bankruptcy starting in October 1997 and relaxing back to normal levels over the next 18 months. If we exclude the data from October 1997 through October 1998, the correlation rises to $\rho = 0.69$.

	ρ	σ_ρ	Intercept	B	σ_B	t-Test
Unemployment Rate SA % (Lag 8)	0.43	0.079	-0.34	0.048	0.0087	5.49

Table 8: Modeling Bankruptcy Filings, YoY %

	ρ	σ_ρ	Intercept	B	σ_B	t-Test
Unemployment Rate SA % (Lag 8)	0.70	0.069	-0.46	0.068	0.0067	10.08

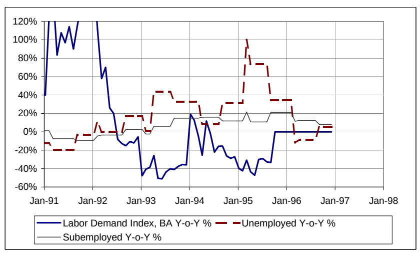
Table 9: Modeling Bankruptcy Filings, YoY %, trimmed for the 1997 bankruptcy law change.

7 Argentina 1995 Tequila Effect

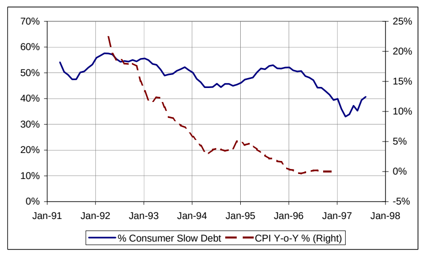
In April 1991, the Argentine government created a fixed relationship between the Argentine Peso and the US dollar in an attempt to stem inflation. The result was almost four years of strong economic growth. However, this period ended abruptly as the Mexican Peso Crisis spilled over into other Latin American economies in what has been termed the Tequila Effect. [14] A financial system crisis occurred in March 1995 with problems in the economy and consumer delinquency shortly thereafter.

Although we could not obtain vintage-level data from this period to analyze, the Argentine Central Bank maintained several measures of consumer delinquency. Figure 15(a) contains a summary statistic called "Consumer Slow Debt". Slow debt is actually a measure of the inventory of delinquent accounts, rather than new delinquencies. As such, the peak correlations to macroeconomic factors will be lagged and longer lasting than one would otherwise expect. For the current analysis, we consider the period from January 1993 through the end of the available data, September 1997, so that we may focus on just the Tequila Effect and avoid inventory spill-over from previous events.

One unique aspect of the Argentine consumer lending environment was the ability of consumers to choose whether to maintain loans and savings accounts in either US Dollars to Argentine Pesos. That meant that as the crisis began, consumers rapidly switched their funds to dollars and would prefer to let Peso-denominated accounts go delinquent rather than move dollars to pesos to make the payments. This results in rapid consumer delinquency at the onset of a crisis, but a long delinquency period as consumers wait to pay-off their debt.



(a) Economic data is from the International Monetary Fund (IMF), International Financial Statistics (IFS) Database



(b) Consumer slow debt data is from the Central Bank of Argentina

Figure 15: Comparisons of consumer-oriented macroeconomic variables to consumer slow debt in Argentina during the Tequila Effect, which followed from the Mexican Peso Crisis.

Also beneficial to a stress testing discussion is that the Argentine government published a range of macroeconomic variables related to consumer financial health.

The crisis was initiated by a flight of capital out of the country, with the corresponding exchange rate and interest rate shocks. A rise in unemployment followed immediately after the economic shock. We considered a range of macroeconomic factors and found several strong correlations among plausibly connected variables. Of course, a model to a single economic cycle will generally exhibit high correlations and low uncertainties relative to what one should expect when multiple economic cycles are available. Any multi-factor model we considered resulted in a lower F-statistic, so a single factor is all this single economic cycle could support, short of performing a principal components analysis in order to combine multiple variables.

All of the variables modeled here had long lead times relative to the slow debt measure. Much of this can be attributed to the fact that slow debt is an inventory measure. Correlating to new slow debt would undoubtedly result in shorter lead times.

	ρ	σ_ρ	Intercept	B	σ_B	t-Test
Ratio Local to Foreign Currency Deposits (Lag 12)	0.67	0.11	0.23	0.16	0.027	5.97
Log 30 Day Interest Rate (Lag 10)	0.68	0.10	0.49	0.25	0.037	6.73
CPI, YoY % (Lag 10)	0.55	0.12	0.44	0.46	0.098	4.71
Unemployed, YoY % (Lag 6)	0.55	0.12	0.44	0.12	0.025	4.75
Labor Demand Index, BA, YoY % (Lag 1)	-0.59	0.15	0.46	-0.10	0.025	-4.06

Table 10: Factors correlated to Argentine Slow Debt with slope and intercept calibrations. ρ is the correlation between the factor and Argentine Slow Debt. σ_ρ is the uncertainty in the correlation. B and σ_B are the scaling coefficient and uncertainty in that whem making a one-factor regression model.

8 Conclusions

Comparing models across multiple recessions allows us to look for consistency in the models created. We found that the same sets of variables provided correlations across different economies and different types of events. Even though very different events are represented here, similar factors appear throughout.

Table 8 arranges the variables according to how much they lead the consumer performance metric. Industry wide time series can be used to find correlations, but problems due to changes in industry originations are present. The DtD Exogenous curves allowed us to normalize individual client data such that the macroeconomic correlations become apparent.

From the table, we can see that GDP and interest rates consistently lead unemployment, and that all appear repeatedly as providing good correlations. House prices appear whenever the data is available, again as a consistently leading indicator. Bankruptcy rates respond so quickly to the economy, that the macroeconomic factors are generally shifted to lagging indicators. However, even strongly correlated lagging indicators can be useful for stress testing.

In this analysis, we were unable to state with certainty what would be the correct transformation of employment / unemployment. The performance metrics being predicted were too varied and the data too short to draw firm conclusions. Looking at interest rates, it seems to be the case that log transforms provide more stability when trying to extrapolate to extreme events, but again the test cases were too short for certainty.

We see that structure in the macroeconomic data must be sought from the consumer perspective. Sometimes no recession will be apparent when consumers have actually experienced a significant event. This was observed clearly in Indonesia. In Canada where no official recessions had occurred in recent years, sufficient structure still existed for the creation of a model.

The exogenous curves derived from vintage data did correlate well to macroeconomic factors, and have proven to be a useful practical way of bringing management intuition into the modeling process. The back-casting approach used to bring portfolio level data into the exogenous curve estimation was extremely helpful in augmenting some of the short data sets in order to better understand the seasonality and long term macroeconomic impacts. Point-in-time measures such as monthly delinquency and default rates always correlate better to macroe-

Lead / Lag	Argentine Industry Slow Debt Time Series	Thai Subprime Card Portfolio Late Delinquency DtD Exogenous	Indonesian Subprime Card Portfolio Late Delinquency DtD Exogenous	Singapore Industry Bankruptcy Time Series	Hong Kong Retail Portfolio Default Rate DtD Exogenous	Canada Industry Bankruptcy Time Series	USA 1^{st} Fixed Mortgage Industry Delinquency DtD Exogenous
12	CDR						
11		GDP	IR				
10	CPI & IR						
9					GDP		
8						UR	
7							
6	UR		UR				
5		IR & HP					
4			CS				
3					CPI		IR
2							
1	LD				HP		
0							UR & HP
-1							
-2					UR		
-3		UR		WPI & GDP			
-4							
-5							
-6							
-7							
-8				UR			

Table 11: Commonly available factors correlating to delinquency, default, and bankruptcy variables. The abbreviations are Interest Rate (IR), Unemployment Rate (UR), Housing Prices (HP), Currency Deposit Ratio (CDR), Consumer Spending (CS), and Labor Demand (LD). The US Mortgage factors are from the multi-factor model described in [3]. This table excludes possible factors for which scenarios are difficult to obtain.

conomic factors than inventory measures like slow debt or cumulative defaults in a year.

The greatest challenge to any stress test modeling is data length. Only one of these examples included two recessions. As such, it is impossible to make statistically rigorous and validated models. The best we can do for now is to seek consistency across economies as cross-validation of the model components.

Acknowledgments

This research would not have been possible without the assistance of several banks and government agencies. In order to protect the confidentiality of the data, we cannot name the individuals at the banks involved, but we thank them for their efforts.

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