Deriving Credit Portfolio Diversification Properties from Large Asset-backed Security Pools

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Abstract

Studies of bank diversification, as well as Basel II regulatory framework, use indirect methods of characterizing the sources of diversification in bank portfolios. The present paper more directly estimates the sources of diversification in thirteen retail credit categories from asset-backed security performance measures that are highly correlated with (unobservable) loan value. Classical Markowitz correlations are derived from almost $1 trillion of asset backed security pools originated by more than five hundred issuers between January 2000 and September 2003. The analysis demonstrates that the performance of many different loan types is weakly correlated, and is sometimes even negatively correlated. Hence, even narrowly focused bank portfolios consisting only of standard retail credits can be constructed to obtain a great deal of diversification. That potential, however, is still not acknowledged in the Basel II regulatory framework.

How risky are opaque bank loan portfolios? That question has vexed academics and bank regulators for some time, leading numerous scholars to compose a broad academic literature on the subject and bank regulators to compose the soon-to-be-imposed Basel II regulatory framework.

Although the Basel II framework attempts, for the first time, to take a modicum of diversification into account in establishing minimum bank regulatory requirements, that approach remains very limited in (at least) four dimensions. First, the Basel II framework breaks loans into only three asset categories: residential mortgages, qualifying retail, other retail.[1] Second, the framework utilizes discreet default correlations within each category, rather than continuous performance correlations that better reflect the expected value of cash flows that determine the Markowitz-style diversification of the portfolio. Third, the framework assigns a single correlation factor to all loans within each category, ignoring potential heterogeneity of different loan products and/or business lines. Last, the framework stops short of adjusting capital requirements for correlations *across* the three categories it does break out, providing no relief for the benefits of cross-category diversification of large multi-line banking companies.

While, the statistical effects of those limitations are presented in Section 1, it is important to realize that the limited approach of Basel II is not entirely without reason. Portfolio risk is measured by the amount of diversification among the assets, which is typically derived from the asset return variance-covariance matrix as introduced by Markowitz (1952; 1959). Bank portfolios, however, have heretofore been difficult to analyze because the variance-covariance properties of bank asset returns have been fundamentally unobservable (because secondary markets for bank assets are thin).

Hence, authors who have previously investigated the diversification properties of bank portfolios have taken an approach of measuring how bank holding company equity betas vary with portfolio composition.[2] There are a number of limitations to this approach. First, portfolio composition in this literature is derived from bank call reports and bank holding company Y-9 reports filed with bank regulators. Those reporting sources aggregate broad asset categories, sometimes in ways that are rather outdated in

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[1] It remains unclear whether the types of loans assigned to each category "fit" with one another. During the Basel II rulemaking process a significant amount of debate occurred over whether to assign home equity loans to "mortgages" or "qualifying retail." Home equity loans were ultimately assigned to "mortgages."

[2] See, for instance, Laeven and Levine (2006), Acharya, Hasan, and Saunders (2006), Stiroh and Rumble (2005), Hughes, Lang, Mester, Moon and Pagano (2003), DeYoung and Roland (2001), and Demsetz and Strahan (1997).

relationship to current product offerings or ways that can confound the assessment of portfolio diversification. For instance, products like derivatives exposures are presented on bank holding company Y-9 reports as gross notional value, divided into held for sale and other categories that do not have a clear-cut definition. It is therefore difficult to relate bank derivatives usage to portfolio diversification.

Second, large actively-traded bank holding companies offer a wide variety of different financial products, some of which are traditional bank products and some of which are newer non-traditional (and prior to Gramm-Leach-Bliley, non-*bank*) products. Bank holding company operations in brokerage services, securities underwriting, insurance, and merchant banking are not adequately characterized on regulatory reports in any way that can effectively capture the individual product or business line correlations that contribute to (or, detract from) diversification.[3]

Third, many traditional bank products are sold soon after origination and therefore do not show up on bank regulatory reports. As of fourth quarter 2004, roughly 68% of total U.S. consumer mortgage debt and 69% of other U.S. consumer debt (Credit Cards, Auto Loans, Student Loans, Home Equity Loans, Manufactured Housing loans, and Other) was securitized, amounting to 68% of all U.S. consumer credit outstanding. Securitized loans influence bank holding company equity returns in some unique, as yet unquantified, manner that has changed across the past couple of decades as banks have increasingly concentrated on servicing credit risk rather than holding credit risk.

Those same loan securitizations, however, have formed a much deeper secondary market for bank assets. While those secondary markets still do not provide loan-level (or even loan pool-level) price data, they do provide continuous loan performance data that is highly correlated with the expected value of the loan (or loan pool). Because the continuous loan performance data is correlated with price, that loan performance data can help yield insight into bank portfolio diversification through the use of classical investment theory. Furthermore, that directly-observed performance data can be used to extract the sources of diversification among major retail credit product investments without having to adjust inferences for agency costs and other influences that may affect bank holding company returns. We contend, therefore, that asset-backed securities yield direct observations of loan performance that can provide new methods of calibrating the

[3] Studies like Laeven and Levine (2006) point out that while there may (or may not) be evidence for diversification discounts, identifying the source of that influence remains elusive due specifically to those types of data constraints (pp. 6-7).

Basel II framework and help academics better understand the sources of diversification in opaque retail loan portfolios.

How much market data can be brought to bear on the measurement of bank diversification? Securitized loan markets are already large and continue to grow fast. Outstanding securitizations of non-mortgage consumer debt grew at a 50% annualized rate across the past two decades, while securitizations of consumer mortgage debt grew at a 15% annualized rate (compare those to overall debt sector annualized growth of 10%).

In levels, as of fourth quarter 2004 there was almost $1.5 trillion of non-mortgage consumer debt asset-backed securities (ABS), $2 trillion of private mortgage-backed securities (MBS), and $3.5 trillion of agency (FNMA, GNMA, FHLMC) MBS outstanding, representing a total market of $7 trillion, or just under 80% of total on-balance sheet bank debt[4] (Federal Reserve Statistical Release Z1, pp. 58-59; Bond Market Association).

Because the fixed income securities originated from that $7 trillion of ABS and MBS conduits are generally offered on public markets a number of ratings agencies and other financial information providers have begun to report aggregate performance data from the underlying pools.[5] The present paper exploits those data to estimate the diversification properties of major retail loan products. Unlike previous literature, the present analysis is not limited to analyzing the risk of a single loan product using portfolio data from one or two banks or analyzing equity returns controlling for limited classifications of bank portfolio characteristics. Instead, the paper analyzes diversification properties directly from securitized pools using almost $1 trillion of the U.S. retail credit market, spanning thirteen major types of loans. The resulting study therefore is not only the first to analyze bank portfolio risk across such a diverse number of assets but also the first to use individual loan portfolio data from so large a number of different lenders.

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[4] It may be more appropriate to look at the market size relative to *all* bank assets, both off-balance sheet (i.e., securitized) and on-balance sheet. Substantial double-counting occurs, however, if one simply adds the securitized assets onto reported bank debt because banks are known to securitize their assets and then buy the securities issued in the private market, ostensibly taking advantage of classifying their loan portfolios as "securities" rather than "loans" for regulatory risk-weighted capital purposes. Notwithstanding that difficulty, the required data does not exist that can accurately measure the proper denominator. Naively adding all securitized assets to reported on-balance sheet assets and re-computing the percentage yields a lower-bound estimate of 40% of bank assets securitized.

[5] There appears to be a sizeable, approximately $0.5 trillion, private placement market industry-wide. There is little data on that market and therefore it is not included in the calculations above.

The results provide new evidence that many retail credit products have very different performance characteristics. Furthermore, some seemingly similar asset classes, for instance auto loans and auto leases, correlate differently with continuous yield or profit measures than they do with discreet default or delinquency measures. Many product correlations are close to zero and some are even negative, suggesting that there exists substantial, previously unmeasured, diversification in retail credit portfolios.

Since this is the first attempt to use asset-backed security data to yield insight into loan portfolio diversification, the estimates provided in the analysis below would not be considered sufficient to recalibrate Basel II. However, we contend that the analysis points to a new method of calibration for the Basel framework and helps regulators and academics better understand the sources of diversification in opaque portfolios. We are confident that as loan markets mature and data improves, approaches similar to the one presented here will be available to provide further insights into loan portfolio diversification.

The rest of the paper proceeds as follows: Section 1 demonstrates statistically that by focusing on default correlations rather than Markowitz correlations, Basel II does not fully characterize fundamental portfolio diversification; Section 2 describes the market data available to derive Markowitz correlation estimates; Section 3 details the screening methods and additive effects pre-processing estimation used to create data appropriate for estimating correlations from the different loan pools; Section 4 presents the results of those estimates; Section 5 summarizes and concludes.

1. Variance of the Aggregated Loan Default Rate with Multiple Loan Categories

This section develops a formal model to demonstrate that the primary determinant of the variation of a loan portfolio is the correlation between the asset classes within that portfolio, whereas the Basel-type default correlations within a given asset class comprise only one component of that correlation. Note that the example used in this section is described in terms of loan default probabilities in order to adhere to a commonly accepted source of value of a loan that has long been the focus of regulatory policy. Nonetheless, probability of default is only one source of variation in the value of a loan or a portfolio of loans. Basel II is taking a step forward in recognizing that probability of default affects loan (or portfolio) value through loss given default. But as Calomiris and Mason (2006) demonstrate, probability of prepayment and reinvestment risk are other sources of value that in some cases can be even more significant (in present value terms) than probability of default and loss given default.[6] Hence, the implications of the model are meant to be extended to all five of the loan performance measures used to create the Markowitz correlations in later sections. See Appendix 2 for a more detailed description of how loan performance maps into the portfolio value of an asset-backed security pool.

Hence, without loss of generality, assume that there are k loan categories with n_i loans in category i, i = 1,…k, and assume that the n_i's are large (that is, there exists granularity in the portfolios). Let N denote the total number of loans, and let $w_i = n_i/N$. If we consider a bank's retail credit portfolio, the loan categories would be asset classes such as auto loans, auto leases, etc.

The default status of the jth loan in category i is denoted X_{ij} where X_{ij} is 1 if the loan is in default and 0 otherwise. Let p_{ij} denote the probability of default for the jth loan in category i. We assume that p_{ij} satisfies the functional relationship
$p_{ij} = P_i + C_i + D_{ij}$ where

(1) P_i is the expected probability of default for category i.

(2) C_i is a random variable with mean 0 and variance σ_i^2 which affects all loans in category i (e.g. a component of C_i could be current interest rate levels, monetary policy, etc.) Thus, C_i can be considered a common, macro-factor that affects all loans within an asset class. We allow this common factor to affect all asset classes separately.

(3) D_{ij} is a random variable with mean 0 and variance σ_D^2 which is specific to the jth individual loan.

All quantities are implicitly assumed to be functions of time, but the interest here is in a cross-sectional analysis so the time index is suppressed for notational simplicity.

The relationship defined above may be regarded as a first order approximation of $E(X_{ij} \mid C_i, D_{ij})$. We assume (as does Basel II) that for any two loans in any two categories, X_{ij} and $X_{i^*j^*}$ are conditionally independent given C_i, C_{i^*}, D_{ij}, and $D_{i^*j^*}$. Intuitively, if the probabilities of default are given for each loan, then, beyond the

[6] We show in that paper that while probability of default and loss given default are indeed costly, they are for the most part explicitly priced in loan interest rates. Prepayment, however, is far more prevalent (and hence far more costly in the aggregate) but is not explicitly priced in loan interest rates. Since determinants of probability of default and probability of prepayment are inversely correlated with one another, the pricing disparity results in a subsidy from the poor to the wealthy.

effects of the common macroeconomic shock, whether or not one loan fails at given time does not affect whether another loan fails at that same time. That is, there is no accelerator or contagion effect. It follows therefore that

$$E(X_{ij} X_{i^*j^*} \mid C_i, D_{ij}, C_{i^*}, D_{i^*j^*}) = p_{ij}\, p_{i^*j^*}$$

The C_i's are assumed to be correlated across loan categories with the correlation between category i and category i* being denoted by ρ_{ii^*}. The D_{ij}'s are assumed to be independent of one another and independent of the C_i's. The assumption that the variance of the D_{ij}'s does not depend on loan category or individual is done for simplicity and does not affect the subsequent conclusions.

The expected aggregated loan default rate is $P_A = \sum_{i=1}^{k} w_i P_i$. The quantities P_i and P_A are estimated from the observed data by $\hat{P}_i = \sum_{j=1}^{n_i} X_{ij} / n_i$ and $\hat{P}_A = \sum_{i=1}^{k} w_i \hat{P}_i$. Our primary interest is obtaining expressions for the variances of these quantities in terms of the σ_i^2, σ_D^2, and ρ_{ii^*}

1.1. Within-category Default Rate Correlation

Within a given category i, the default probabilities are correlated due to the presence of the common factor C_i. The covariance and correlations are:

$$\operatorname{cov}(p_{ij}, p_{ij^*}) = \sigma_i^2$$

$$corr(p_{ij}, p_{ij^*}) = \sigma_i^2 / (\sigma_i^2 + \sigma_D^2)$$

This strength of the correlation is determined by the ratio of the common-factor variance and the variance of the individual default rates. Varying conditions may make this large or small. It will be shown that these correlations have virtually no effect on the variances of $\hat{P}_i$ or the estimated aggregated default probability $\hat{P}_A$ if the common factor C_i is non-negligible.

1.2. Within-category Variance of the Estimated Default Rate

Because X_{ij} is a Bernoulli random variable,

$$E(X_{ij} \mid C_i, D_{ij}) = p_{ij} \text{ and } Var(X_{ij} \mid C_i, D_{ij}) = p_{ij}(1-p_{ij})$$

In the computations below, we will need to condition on a subset of the D_{ij}'s which we will denote by $\{D_{ij}\}$. The conditioning subset will be obvious from the context. Thus

$$E(\hat{P}_i \mid C_i, \{D_{ij}\}) = P_i + C_i + \sum_{j=1}^{n_i} D_{ij} / n_i$$

Therefore,

$$Var(\hat{P}_i) = E(Var(\hat{P}_i \mid C_i, \{D_{ij}\}) + Var(E(\hat{P}_i \mid C_i, \{D_{ij}\})$$
$$= [E(\sum_{j=1}^{n_i} p_{ij}(1-p_{ij})/n_i^2)] + [\sigma_i^2 + \sigma_D^2 / n_i]$$
$$\approx \sigma_i^2$$

Because $p_{ij}(1-p_{ij}) \leq 1/4$, the first term on the right is bounded $1/4n_i$, and because n_i is large, the dominant term is the common factor variance σ_i^2. No matter how diversified the individuals loans are within the category, the volatility of the default rate is determined almost entirely by the variance of common factor C_i.

This is an important result when we consider the current status of the Basel treatment of retail credit. Basel assumes that the assets within the three types of retail credits, Mortgages, Qualifying Revolving, and Other, are identical. The above result, however, shows that if there is a correlation among different asset classes due to some common factor, the retail credit portfolio may or may not be diversified depending upon the correlations of the asset classes due to the common factor.

1.3. Between-category Correlation of the Estimated Default Rate

Using the conditional independence of the X_{ij}'s, the covariance of $\hat{P}_i$ and $\hat{P}_{i*}$ is computed as:

$$E[E[(\hat{P}_i - P_i)(\hat{P}_{i*} - P_{i*})] \mid C_i, C_{i*}, \{D_{ij}\})] = E[(C_i + \sum_{j=1}^{n_i} D_{ij} / n_i)(C_{i*} + \sum_{j=1}^{n_i} D_{i*j} / n_{i*})]$$

$$= E(C_i C_{i*}) = \sigma_i \sigma_{i*} \rho_{ii*}$$

The correlation is ρ_{ii*}.

1.4. Variance of the Estimated Aggregate Default Rate

For a two-asset portfolio,

$$Var(\hat{P}_A) = \sum_{i=1}^{k} w_i^2 Var(\hat{P}_i) + 2\sum_{i<j} w_i w_j Cov(\hat{P}_i, \hat{P}_j).$$

Because $Var(\hat{P}_i) \approx \sigma_i^2$, it follows that

$$Var(\hat{P}_A) \approx \sum_{i=1}^{k} w_i^2 \sigma_i^2 + 2\sum_{i<j} w_i w_j \sigma_i \sigma_j \rho_{ij}$$

Thus, the variance of the aggregated loan default rate is determined almost entirely by the variances of the category factors and correlations between them. Since it was shown above that those category factors and correlations between them, in turn, are primarily a function of the global or macro effects of C_i, then it is straightforward to conclude that those global or macro effects, not the mixture of loans within a category, determine the volatility of the loan default rate as long as those common factors C_i are not negligible.

This is the same result that is obtained from Markowitz (1952; 1959): It is not the number of loans that determines the diversification of the loan portfolio, but rather the correlation of the asset classes within that portfolio. Thus, as we have discussed, it is important to examine asset correlations in order to adequately determine the diversification that exists within a loan portfolio.

1.5. Special Case of Two Categories and Equal Variances

In the case of two categories with equal variances $\sigma_1^2 = \sigma_2^2 = \sigma^2$, the variance of the estimated aggregate default rate is

$$Var(\hat{P}_A) \approx \sigma^2 (w_1^2 + w_2^2 + 2w_1 w_2 \rho_{12})$$

The correlation goes from σ^2 to $\sigma^2 (w_1 - w_2)^2$ as the correlation goes from 1 to -1 with the minimum of 0 occurring when the weights for the two categories are equal. Again note that there is no dependence on σ_D^2.

Again, this result has important implications for the Basel capital standards as it is assumed that the categories within the retail credit portfolio are identical. This result shows that even if the categories have identical individual default properties, the correlation of the asset classes, rather than the correlation of defaults within the asset classes, will determine the overall value of the entire loan portfolio.

2. Data Description

2.1. Data Source and the Sample's Relationship to the ABS and MBS Market

The present section describes the asset-backed security performance data that is used to estimate the kinds of Markowitz-style portfolio correlations that are important to bank diversification. Recall that while loan or loan pool prices are not available for the retail loans included in the analysis, loan performance measures that are correlated with loan price should provide correlation estimates that are similar to market returns (if those existed).[7] Robustness is tested by estimating correlations from five different loan performance measures. The following section describes the data source and data

[7] One may be tempted to argue that since the aggregate value of all tranches (including any residual tranches) equals the total value of the asset-backed loan pool, in theory if one obtained the prices of each tranche and their issuance volumes, one could sum their market values to get the market value of the loan pool. Then, estimates of the covariance of changes in the market values of different pools over time could be obtained. In practice this technique would not likely yield reliable value estimates for two reasons. First, few senior, much less junior, tranches are actively traded, so price data for those is not likely to be very meaningful. Second, residual tranche valuation is farugh with difficulties, as evidenced by the role residuals valuation has played in the vast majority of bank failures since securitization became popular in the mid-1990s. Hence, that method is not likely to yield meaningful insights.

properties in general detail. Subsequent sections describe the statistical properties of the data and estimate the correlations.

The asset-backed security performance data come from servicer reports aggregated by ABSnet. Servicer reports are monthly reports on collateral performance that are provided for publicly issued asset-backed securities. Servicer reports may be at the individual loan level, the pool level, or the security level.[8] Starting in 2006, Securities and Exchange Commission Regulation AB will begin to require more systematic and detailed servicer reports on collateral and performance.[9] As yet, however, there are few standards for servicer report format or content and while SEC Regulation AB requires reporting, it will not impose standards on firms reporting ABS performance.

ABSnet puts pool-level servicer reports in a single repository, though not necessarily one that is suitable for research. Therefore it was necessary to individually query all active server page (ASP) reports provided by ABSnet for all available issuers and compile them into flat files for each collateral class. That exercise yielded nearly 250,000 pool-month observations, from early 1992 to September 2003, on 8,884 securitized loan pools involving 22 collateral asset classes.

During the early period of the sample, relative few sectors are active. By 2000, the ABS market for all of the collateral classes had matured to the point where analysis across the majority of asset classes is feasible. Nine asset classes, however, still have too few time-series observations and/or too few issuers (in some cases only a single issuer) to analyze without substantial issuer-specific bias.[10] Hence, correlations are estimated for the following thirteen asset classes: Auto Loans, Auto Leases, Credit Cards, Commercial Mortgages, Dealer Floorplans, Equipment Leases, Marine and Boat Loans, Manufactured Home Loans, Other Consumer Loans, Recreational Vehicle Loans, Student Loans, Residential Mortgage Loans, and Home Equity Loans.

Table 1 shows that even after paring the sample down to pools outstanding during the period 2000-2003, there are 6,266 pools that were outstanding at any time in the

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[8] Loan-level servicer reports are common for agency mortgage-backed security issues. A pool is a collection of loans that form the basis for a tranched security issue.

[9] See http://www.sec.gov/rules/final/33-8518.pdf for details.

[10] Given that the goal is to determine correlations across different asset classes and not issuers, *per se*, including classes where there is only a single issuer at any given point in time would introduce a high degree of issuer-specific risk into the estimates. Thus, CDOs, Franchise Loans, Insurance Premium Loans, Motorcycle Loans, Other, Small Business Loans, Time Share Loans, Trade Receivables, and Truck Loans are excluded in the analysis that follows.

period. Those pools comprise a total outstanding balance of over $960 billion of the $3.5 trillion (as of fourth quarter 2004) private ABS and MBS market.

2.2. Sample Composition

Table 1 shows that the most pools in the sample involve Home Equity Loans (2,559 pools), followed by Residential Mortgages[11] (1,673 pools), Commercial Mortgages (510 pools), Credit Cards (504 pools), Auto Loans (430 pools), Manufactured Homes (260 pools), and Equipment Leases (113 pools). Dealer Floorplans, Student Loans, Other Consumer Loans, Recreational Vehicles, Auto Lease, Marine and Boat collateral classes involve less than 100 pools apiece.

Pools in different collateral sectors vary widely, however, in size. Home Equity Loans, ranks 1st in number of pools, ranks 10th in average pool size at about $250 million. Credit Cards, ranked 4th in the number of pools, ranks first in average pool size at more than $20 billion.

The reason for such large average pool sizes in the Credit Card sector is because those pools are structured as revolving pools instead of traditional amortizing pools, and the high-volume nature of credit card receivables growth has resulted in heavy reliance on Master Trust and Issuance Trust structures.[12]

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[11] Note that these are only private Residential Mortgage securitizations. Government sponsored enterprises are not covered by the database, and are therefore not included in the present analysis.

[12] Revolving pools are constructed to accommodate assets with short maturities, common among Credit Cards and Dealer Floorplans. By replacing loans in the pool as they pay off over some stipulated time period (called the revolving period) the issuer can sell securities with maturities longer than those of the average loan maturity in the pool. In that way, securities with maturities of three to five years can be backed by, for instance, credit card loans that have an average maturity of about six months. Revolving features have implications for the results that follow since the addition of new loans to an existing pool may obscure vintage effects that are typical of pure amortizing pools. In the work that follows, asset correlations are constructed using all available data instead of, say, constructing an index from a sample of issues, which reduces potential vintage bias.

Master Trusts and Issuance Trusts offer scalability by standing as a ready conduit for subsequent loan sales and securitizations, much like a shelf registration provides the legal foundation for expanding traditional equity or bond issuance. Here, however, the Master Trust itself is the legal entity issuing the securities, whereas the shelf registration is just a legal filing. It is important that the legal entity, the Trust itself (whether a Master Trust or Issuance Trust), be brain-dead and therefore tax-free (that is, not classified as an investment company under the Investment Company Act of 1940) in order to maintain a profitable sale and repackaging of claims against the pool of loans being securitized. Hence, a Master Trust is a specially-designed legal entity that can grow while remaining brain-dead and tax-free.

Master Trusts and Issuance Trusts also offer diversification across pools through legal features that promote risk socialization. Under a socialized Master Trust structure, new pools of loans bought by the Master Trust each period remain discreet, but the securities sold to investors to finance the purchase of that new pool may be backed by all the pools owned by the Master Trust. At first glance, this structure would appear to increase risk to the investor, since if the issuer increased the riskiness of their

2.3. Sample Breadth

The 524 issuers in the sample, listed in Appendix A, cover a wide range of industry underwriting practices (i.e., subprime versus prime focus) and vintage properties. That range can be observed readily by looking at the 90-day Delinquent Balances as a Percent of the Pool Balance in each collateral area.

For Mortgages, RMAC (a well-known deep subprime lender) has the highest 90-day Delinquent Balance in one pool at 100%, followed by Homeloans PLC at 38%. Fleet has one pool with a 30% 90-day Delinquent Balance. Wells Norwest (a well-known prime lender) is among the lowest in terms of 90-day Delinquent Balances at 0.0276%, with GMAC, Washington Mutual, Countrywide, and Citibank only slightly higher.

Home Equity Loans typically have higher 90-day Delinquent Balances than first-lien Mortgage-backed Securities, in part because of the junior lien position of the loan and also in part because of the subprime focus of the industry. At the high end of 90-day Delinquent Balances are United Companies Financial Corp. and Ocwen Financial, at about 20%. Cityscape and ContiMortgage come in at just over 10% (although ContiMortgage has one pool at 37%). C-BASS and Delta Funding are at about 4%, Norwest and The Money Store about 3%, Advanta, Master Financial, Mego Mortgage, and DiTech about 1.5%, Aames and Countrywide about 0.75%, and Ameriquest, RFC, and GMAC below 5%. Bank of America, Chase, Wells Norwest, and Wachovia all report 0.00%.

Although the maximum 90-day Delinquent Balances for Credit Card loans are lower than those for Home Equity, Credit Cards typically have consistently higher 90-

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underwriting strategy the risk of all securities would increase. Nonetheless, while socialization may result in adverse consequences if there exist vintage effects among strictly amortizing pools, since Credit Card pools revolve and therefore new loans are being added into all pools on a periodic basis anyway, no new risk is introduced through socialization.

Master Trusts and Issuance Trusts have been the mainstay of issuance in the Credit Card sector since the mid-1990's. Since that time, the scalability and socialization in revolving pool structures have resulted in Master Trusts and Issuance Trusts that are quite large, because those trusts have come to include nearly all securitized loans for any particular issuer. In this manner, the issuance trusts of large Credit Card issuers like MBNA (just under $60 billion) and Citibank (just over $50 billion) and others inflate the average pool size in the credit card sector.

Furthermore, since Master Trusts and Issuance Trusts contain many pools of loans that are all lumped together through pool socialization, the data source repeats aggregated performance data for each pool in the trust (and there can be quite a few in the large issuance trusts of issuers like MBNA and Citibank). Hence, repeated performance observations across those socialized trusts are omitted in the analysis that follows by excluding all but one pool-month observation for groups in which the performance measure equals the issuer pool mean.

day Delinquent Balances than Home Equity Loans. The highest in the sample is Fingerhut at 13.21%, followed by Spiegel at 6.48% (Spiegel restructured its trusts in 2001 and in early 2003 Spiegel/First Consumers National Bank agreed with the Office of the Comptroller of the Currency to sell or liquidate the First Consumers National Bank credit card portfolio by 30 April 2003). Chevy Chase, BancOne, and First Chicago follow at the 3% range, Associates and Capital One at 2.5%, Chase and First USA at 2%, and MBNA and Citibank at about 0.66%.

Automobile Loans tend to have 90-day Delinquent Balances similar to Credit Cards. The highest reported 90-day Delinquent Balance rate is the 4.27% reported by National Acceptance, followed by 4.22% at Summit Acceptance. Another eight issuers, including Boatmans, AmeriCredit, Barnett, Nationsbank, and BancOne, reported 90-day Delinquent Balances greater than 1%. Fifteen reported 90-day Delinquent Balances greater than 0.10% but less than 1%. Thirty, including all the captive automobile finance companies except Hyundai, reported 90-day Delinquent Balances below 0.10%.

Automobile Leases tend to have very low 90-day Delinquent Balances. Ford and Honda report 90-day Delinquent Balances on the order of 0.10%, while Nissan, FACT, and VCL report 0.00%.

Similarly, Dealer Floorplan loans (loans used to finance automobile dealer inventory) tend to report very low 90-day Delinquent Balances. Even Conseco and Greentree, known subprime lenders, report 90-day Delinquent Balances of only 0.04% in the Dealer Floorplan sector. Like Automobile Loans and Automobile Leases, since the collateral, in this case new, unsold, automobiles, is very easy to seize and liquidate most problem loans may never go to 90-days.

Equipment Leases are similar to Dealer Floorplans in that they also have very low 90-day Delinquent Balances. Nonetheless, there are a few outliers in this sector, such as Advanta at 4.70%, Textron Finance at 4.60%, and Heller Equipment at 3.66%. Surprisingly, DVI, Inc. reports 90-day Delinquent Balances of only 0.62% and 0.28%.[13] CIT, a well-known prime equipment lease company, reports 90-day Delinquent Balances at 0.22%.

[13] DVI went into bankruptcy on 26 August 2003, after which DVI was accused of serious improprieties in connection with its securitization of medical Equipment Leases. In particular, it is alleged that DVI consciously (i) double-pledged assets, (ii) used ineligible or "out-of-compliance" collateral to obtain advances from Fleet, the provider of one of its main credit lines, and (iii) practiced "round-trip financing." Experts for the bankruptcy court assert that DVI engaged in fraudulent activity from 1999 through its bankruptcy filing in May 2003.

The Commercial Mortgage sector is characterized by very low 90-day Delinquent Balances. The one exception is Wilshire Credit, reporting 38% 90-day Delinquent Balances. Other issuers, including PNC, Lehman, First Boston, Fannie Mae, DLJ, Amresco, GMAC, GE Capital, Bear Stearns, and Nomura al report 0.00% 90-day Delinquent Balances. Those low 90-day Delinquent Balances result from the low granularity and relative lack of development for the CMBS sector; less granular, less developed sectors only securitize the safest loans.

Student Loans tend to report stable, but positive, 90-day Delinquent Balances. The highest in the sample is Wells Norwest, reporting 1.76%. Sallie Mae and SMS report 1.73% and 1.24%, respectively. The inability to discharge Student Loans in personal bankruptcy helps keep 90-day Delinquent Balances low and stable.

Recreational Vehicle Loans and Marine/Boat Loans also report fairly low 90-day Delinquent Balances, the highest being Nationscredit at 0.79% for Recreational Vehicle Loans and CBNJ at 3.59% for Marine/Boat Loans.

The Other Consumer Loans category is a catch-all, and performance is reflective of that categorization. The highest 90-day Delinquent Balances is reported by Paragon Personal Loans at 7.5%, followed by Conseco Recreational Equipment Loans at 1.35%.

Manufactured Housing, despite its reputation as the worst performing ABS sector for investors since the demise of gain-on-sale accounting in 1998, reports 90-day Delinquent Balances similar to some other viable sectors. United Companies Financial Corporation (which sought bankruptcy protection in 1999) reports 90-day Delinquent Balances at 8.26% on their Manufactured Housing Loans, while Wilshire Funding and Indy Mac follow at about the 5% level. Conseco, viewed as one of the scoundrels of the industry shakeout after seeking bankruptcy protection in 2002, reports 90-day Delinquent Balances at only 0.92%.[14]

2.4. Data Section Summary and Performance Variables of Interest

Classic Markowitz (1952; 1959) portfolio theory produces correlations among asset returns by computing:

[14] Recall, however, that the biggest shock from the Conseco case was not the deterioration of the assets but rather the re-writing of the waterfall for investors in Conseco's bankruptcy proceedings.

$$\sigma_{\text{port}} = \sqrt{\sum_{i=1}^{n} w_i^2 \sigma_i^2 + \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \text{Cov}_{ij}}$$

where :
σ_{port} = the standard deviation of the portfolio
w_i = the weights of the individual assets in the portfolio, where weights are determined by the proportion of value in the portfolio
σ_i^2 = the variance of rates of return for asset i
Cov_{ij} = the covariance between the rates of return for assets i and j.

The theory goes on to show that as the number of assets in the portfolio increases, the sum of the weighted asset variances, $\sum_{i=1}^{n} w_1^2 \sigma_i^2$, grows arithmetically while the covariance terms, $\sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j Cov_{ij}$, grow exponentially. Hence the covariance terms quickly dominate the magnitude of the resulting portfolio variance. Since the covariance terms may be rewritten as

$$\text{Cov}_{ij} = r_{ij} \sigma_i \sigma_j .$$

where :
r_{ij} = the correlation between the rates of return for assets i and j.

Therefore Markowitz maintains the correlations among assets in the portfolio are the primary determinant of portfolio *diversification*.[15]

Markowitz' result is the final summary of the mathematical model of the Variance of the Aggregated Loan Default Rate with Multiple Loan Categories presented in Section 1. The model in section 1 may be thought of as a variant of Markowitz portfolio theory, with asset variance (D_i) diversified away in the aggregate portfolio so that the correlation is determined almost entirely by the variances of the category factors and

[15] See standard textbook references. For instance, Reilly and Brown (2006), p. 211, explains that "…the important factor to consider when adding an investment to a portfolio that contains a number of other investments is *not* the new security's own variance but *its average covariance with all the other investments in the portfolio*." Since the present analysis is only interested in measuring diversification value it is focused on estimating correlations rather than the individual asset return variances.

correlations between them. Those category factors and correlations between them, in turn, are primarily a function of the global or macro effects of C_i. Hence, it is concluded that those global or macro effects, not the mixture of loans within a category, determine the volatility of performance as long as those common factors C_i are not negligible.

Recall that there does not exist an active market for whole loans for the majority of typical loan products. (Since the purchasing Trust is often initially capitalized by the entity that originally issued the loans, even whole loan prices are often not a useful indicator of market value.) Hence, the present paper does not rely directly on loan price data. Instead, the analysis relies on a large broad data set of loan performance data from securitized pools of loans.[16]

The analysis proceeds, instead, under the assumption that in the presence of sufficient information, prices in efficient markets should be derived from fundamental performance. Hence pool performance can reasonably be expected to correlate with price. Therefore, pool performance correlations can proxy for asset price correlations. While it is impossible (without market-derived loan prices) to use a multivariate approach to mapping performance into price (as in, say, Calomiris and Mason 2006), the analysis that follows confirms that even if the performance measures analyzed are only partial determinants of price, reasonably appropriate performance measures produce correlations that broadly agree with one another, reinforcing the conclusion that there exists a surprising amount of diversification in typical retail loan portfolios.

Depending on the asset class, there are either 98 or 181 performance data fields available in the ABSnet data.[17] Most pools, however, will have complete data only for 10 to 15 of those fields (and not necessarily the same 10 or 15 fields). Of those performance measures for which data are available, variables are chosen for analysis on the basis their relevance to pool value. Appendix B describes specifically how asset performance maps into pool Excess Spread triggers that guard against default for ABS and MBS investors and, hence, how pool performance maps into cash flow value for investors. Since pool performance characteristics determine directly market value for investors in the derivative securities, correlations among those performance characteristics should

[16] Note that there is no asset-backed security price series that can help us with the task, as those securities tranche or otherwise decompose fundamental asset risk. As a result, for instance, AAA securities are correlated with interest rates and other tranches are correlated with collateral to varying degrees as affected by tranche positions and credit enhancements. The point is, tranching and decomposition obfuscates fundamental asset correlations. Hence, ABS price quotes (even if they existed for such a broad sample, which they do not) are not useful for computing underlying asset correlations. See also footnote 7.

[17] Revolving credit assets, such as credit cards and dealer floor plans, have 98 performance measures. All other asset classes have 181 performance measures.

yield insight into correlations among the values of different classes of assets in large credit portfolios.

The performance measures analyzed in this study include 90-day Delinquent Account Balances as a percent of the total securitized balance, Net Loss Rates on the total securitized balance, Payment Rates, Pool Yields, and Excess Spreads. Performance correlations are derived from either 43 or 44 time-series observations, depending upon whether the sector reported their September 2003 data at the time of collection.

Table 2 contains median pool-month values and sample sizes for the performance measures analyzed.[18] First, note that commonly reported performance measures vary by asset class. For example, Commercial Mortgages reported 11,072 pool-month observations for the 90-day Delinquent Balance, but only 22 pool-month observations for the Excess Spread. That difference arises because Commercial Mortgages, Home Mortgages, and Equipment Leases do not typically report Excess Spread.

In general, the performance variable with the highest reported frequency is the 90-day Delinquent Balance. The median values of Pool Yield, 90-day Delinquent Balances, and Net Loss Rates tend to correspond with known risks across the asset classes. For example, Other Consumer Loans have the highest median Pool Yield (0.2264) followed by Credit Card Loans (0.1884). Student Loans (0.0654) and Residential Mortgages (0.0724) are the lowest median Pool Yields. Manufactured Home Loans have the highest median 90-day Delinquent Balances (0.0144) and Credit Card Loans have the highest median Net Loss Rates (0.0567).

There is also substantial evidence of variability in the median performance measures across time for each of the asset classes examined. Appendix C contains graphs of the performance measures over time for each of the asset classes. One of the more interesting graphics in Appendix C is for Manufactured Home Loans (Appendix C, Figure C8). This graphic shows the collapse in credit quality in that sector beginning in roughly December 2002. At that date, Net Loss Rates and 90-day Delinquent Balances increase and Excess Spreads fall as lenders in the Manufactured Home sector realized abnormally low returns from overly liberal lending policies in the mid- to late-1990s.

[18] Median values are reported in order to accommodate the presence of idiosyncratic outliers in the raw data set. The treatment of those extreme values will be discussed in the next section.

3. Data Screening and Pre-processing

So far only the raw data from the securitized pools has been presented. That data is an unbalanced panel. After removing repeated observations reported for revolving Master Trusts (see footnote 12), three additional transformations to the data need to be undertaken before it is suitable for producing meaningful correlations series. First, since the data has never before been used and cleaned, it is screened for extreme observations. Then, since old pools mature and new pools begin inside the data window, the data is screened for adequate time-series length in the pools to ensure observational stability. Last, an additive effects interpolation and extrapolation method is implemented to fill in missing observations caused by pools beginning and ending at various time periods and generate a balanced panel across the entire history of the data.

The additive effects interpolation and extrapolation method is generally related to interpolation and extrapolation problems posed by Friedman (1962) and later modified by Chow and Lin (1971) and to correlation forecasting routines implemented in literature by Elton and Gruber (1973), and more recently Chan, Karceski, and Lakonishok (1999) and Elton, Gruber, and Spitzer (2005). Unlike the applications implemented by previous authors, the present approach does not seek to forecast correlations of individual firms or issuers, but merely transforms an unbalanced panel that has missing data and occasional outliers (that create intermittent missing data whe removed) into a balanced panel data set that can be used to compute observationally stable correlations for broad credit sectors across the time period. Hence, biases that may be induced by the interpolation and extrapolation process for individual firms or issuers are averaged out in the panel prior to estimating the asset correlations. The resulting panel is used to estimate correlations of the average performance measure for each asset class.

3.1. Data Screening

3.1.1 Screening for Extreme Observations

Screens for extreme observations for each of the individual performance measures are implemented based upon reasonably probable ranges of those variables. For Pool Yield, Net Loss Rate, and Excess Spread the screen requires the measures to have a value between -100.0% and 100.0%. For the 90-day Delinquent Balance percentage and the Payment Rate, the screen requires the measures to have a value between 0.0% and 100.0%.

For observations outside those bounds, a Lexis-Nexis search confirmed that the outliers outside the rational bounds are genuine data errors rather than unique events that may significantly affect the correlation estimates. As a result, the data points were deleted and the vacant cell treated the same as a missing value. Then, the estimation model is allowed to fill the missing values created by the extreme observation screen as discussed in Section 2.2.

We also investigated idiosyncratic outliers within the rational bounds established above. We consider the outlier to be an idiosyncratic only if the observation is both extreme *and* accompanied by an extreme jump in performance. In that manner, the other extreme observations within the rational bounds are established as genuine and are therefore retained in the data set.

3.1.2. Screening for Adequate Time Series Length

Screening for adequate time-series length includes pools that begin within a reasonable distance in time from the start date of the sample and eliminates pools with too few reported time-series observations to be of significant influence. One way to screen for time-series observation length would be to require that a pool have a *complete* time-series of observations for the whole sample period, i.e., by including only pools that have at least 43 months to maturity and were issued prior to the beginning of the sample period (January 2000). Such a strategy, however, would yield a small sample size and, given the fixed maturity aspect of the pools, suffer from significant survivorship and vintage biases.

Three time-series screening mechanisms of varying stringency are implemented in the results that follow. The three data sets are generated by requiring that each pool have at least six, twelve, or twenty-four monthly time-series observations for the performance measure being studied. Estimating the correlations using those three different time-series screens in conjunction with the extreme value screen provides a sensitivity test of the time-series adequacy screen, showing how the number of actual observations used affects the correlations computed. Again, the goal is to use as much data as possible to fill in systematic missing observations arising from new pools entering and old pools exiting during the observation period and fill in occasional nonsystematic missing observations arising from the extreme value screen while maintaining estimation accuracy.

3.1.3. Comparison of Raw, Extreme Value Screened, and Time Series Screened Data

A total of six data sets are analyzed, including each of the three time-series screens with and without the extreme observation screen, in order to test for robustness.[19] Overall, results using the six observation screen are qualitatively similar to those computed with more stringent time-series adequacy screens and the inclusion of extreme observations gives misleading results. Hence, the present manuscript reports results for data that has at least six observations for each performance measure and screened for extreme observations. Results using the five other screen combinations are available on request.

Appendix D, Tables D1 – D5, illustrates the sample attrition arising for each of the performance measures with a six-period time-series adequacy screen. For each asset class, Appendix D, Tables D1 – D5 report: Asset Class, Original Number of Observations, Number of Extreme Observations Replaced, Number of Observations Lost Due to Requirement of Six Observations, Number of Observations Lost Due to Elimination of Multiple Series in Master Trusts, Final Number of Observations Used in Estimation, and the Final Number of Pools.

The number of observations lost due to elimination of duplicate master trust pools is largest for Credit Cards and Dealer Floorplans, although there is also some effect on Residential Mortgages, Home Equity Loans, Other Consumer Loans, and a few Equipment Lease pools.

The extreme observation screen eliminates the most observations for Residential Mortgage Loans and Home Equity Loans. However, as a percentage of all observations, the number of extreme observations is small for all asset classes.

The least restrictive time-series adequacy screen, requiring at least six observations for each performance measure, tends to eliminate only pools that have absolutely no data reported over the January 2000 to September 2003 time period.

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[19] Six time-series observations, no extreme value screen; six time-series observations, extreme value screen; twelve time-series observations, no extreme value screen; twelve time-series observations, extreme value screen; twenty-four time-series observations, no extreme value screen; twenty-four time-series observations, extreme value screen.

Nonetheless, Appendix D, Tables D1 – D5 show that even that minimal screen deletes a non-trivial number of pools.

3.2. Data Pre-processing: Additive Effects Interpolation and Extrapolation Estimation and Results

3.2.1. Additive Effects Interpolation and Extrapolation Estimation

The present approach differs from previous research that has examined the calculation of Markowitz correlations across fixed-income assets. Previous research has generally relied on two sources for data: fixed-income index returns and/or bond series where a long history of consistent maturity bonds exist (e.g. government bond series). The present data has neither a consistent index nor long histories of pools with consistent maturities. The present data does not include returns nor a constant maturity series, so typical methods of analysis are not possible.

Other less traditional studies, such as Jacob, Graham, and Tilley (1987) and Mulvey and Zenios (1994), attempt to estimate future fixed-income prices based on estimates of the future yield curve. Again, that approach is not possible with the present data for at least two reasons. First, the data contains a wide variety of maturities as well as a great deal of dispersion in yields due to issuer quality and pool quality. Thus, both differences in maturities and differences in issuer quality would have to be controlled for. Second, the present data do not include price: the analysis instead infers price movements that are correlated with performance data. The impact that yield curve changes would have on the performance measures has not yet been established. Those data limitations preclude a dynamic analysis of yield curve changes.

The unique nature of the present data set necessitates a new approach. Hence, an additive effects interpolation and extrapolation method is applied to the data to estimate the value of missing observations and fill in the missing data points within the panel, and then calculate the correlations in a straightforward fashion as for equities. One of the major advantages of estimating an additive effects procedure on a large data set such as ours is that valid least squares estimates of the mean values of the performance measures across the different pools and across time can be computed. In computing those least squares estimates across time and different pools, the process implicitly accounts for potential changes in the performance measures both due to shifts in the yield curve over time and for differences in performance in different pools due to heterogeneous issuer quality, in addition to controlling for missing data.

The additive effects procedure is derived from a fundamental fixed-effects estimation strategy with panel data. In the present application, intercepts are allowed to vary for each pool while time has a common effect across all pools. The model is specified as:

$$Y_{i,t} = \sum_{i=1}^{I} a_i \times (pool_{i \in I}) + \sum_{t=1}^{T} \lambda_t \times (month_{t \in T}) + \varepsilon_{i,t} \qquad (1)$$

where the individual group effects are the a_i's and the common time effects are the λ_t's.

The computed fixed effects depend only on deviations from the group means. Hence, the fixed effects estimations produced by the additive effects procedure are ideal for generating least-squared predicted values for missing observations that can help the panel produce a consistent monthly time-series of *average* performance *for each asset class* that can be used to compute the Markowitz portfolio performance correlations (see, for instance, Davidson and MacKinnon 1993).[20]

Equation (1) is estimated by a generalized linear model individually for the thirteen asset classes in each of the five performance measures. Least-squared mean predicted values based on the estimated coefficients are used to interpolate and extrapolate missing observations in the panel. The mean monthly performance series from the interpolated and extrapolated panels for each asset class are used to compute Markowitz portfolio correlations for each of the five performance measures. The six data sets (one from each time-series/extreme value screening method) are used to calculate six sets of asset correlations. Only results for the six-observation screen without extreme values are presented below. Results generated by the other five other data sets are available from the authors upon request.

[20] The fixed effects estimators, however, may not produce reliable point estimates of *individual pool* performance that could, for instance, be used to compare directly idiosyncratic issuer-level or pool-level performance differences. The authors are employing a more sophisticated estimation approach in order to compare directly those idiosyncratic differences between issuer underwriting strategies and diversification benefits accruing to those differences. Those point estimates, however, will be much more sensitive to outliers, heteroskcedasticity, and autocorrelations than the relatively simple aggregate means estimated in the present analysis.

3.2.2. Additive Effects Estimation Results

Tables 3 - 7 contain the results estimating equation (1) for each of the performance measures (Pool Yield, 90-day Delinquent Balance, Net Loss Rate, Payment Rate, and Excess Spread, respectively) in the 13 asset classes. Note that the pool class variable explains a significant amount of variation in the performance measures in all of the five performance measures examined. Hence, as would be expected, there are differences in the performance measures across pools within each asset class. The time variable also explains a significant amount of variation across all five performance measures for most of the asset classes, consistent with Appendix C, Figures C1-C13.

The r-squared values in the models of equation (1) are high across all asset classes for most of the performance measures. Hence, the variation in the performance measures within an asset class is largely explained by fixed effects differences in issuers and time.

While the results from estimating equation (1) are fairly similar for each performance measure and each asset class, there are some differences that are worth noting. The model seems to explain the most variation for Credit Cards for all performance measures except Excess Spread. The model explains the least variation for Auto Leases, again with the exception of Excess Spread. For Excess Spread, r-squareds are highest for Other Consumer Loans and Residential Mortgages and lowest for Marine and Boat Loans and Recreational Vehicles.

The time class variable performs well in nearly all asset classes for all performance measures except Net Loss Rate. In the Net Loss Rate models, the time class variable explains less variation for Auto Leases, Commercial Mortgages, Dealer Floorplans, Equipment Leases, and Other Consumer Loans. That result, however, is not surprising since Net Loss Rate shows little variation over time in those asset classes in Appendix C, Figures C1, C4, C5, C6, and C9, respectively.

3.2.3. Comparison of Raw Data and Additive Effects Estimation Results

Table 8 contains mean performance measures from the raw data and from the model estimation for each asset class.[21] The mean performance measures estimated from the

[21] Note that since the model results are derived from the raw data, the samples from which the means are drawn are not independent. Furthermore, random sampling for pairwise tests may induce bias due to issuer selectivity. Hence, there are no applicable statistical tests of the differences between the reported means presented in Table 8.

raw data differ from those estimated by the additive effects procedure by more than 0.01 in only 10 of the 60 cases estimated. Hence, the additive effects estimates do not deviate dramatically from the raw data. Furthermore, the means from the additive effects procedure estimates also do not deviate dramatically from the raw data medians in Table 2, only 19 of 65 cases deviating by more than 0.01. Thus, the screens and additive effects estimation procedure do not appear to significantly alter the point estimates nor the distribution of the data used to compute the correlations.

Where deviations do occur, they are isolated to a few performance measures and a few asset classes. Estimates for the Payment Rate suffer worst because the Payment Rate models in Table 6 had the lowest r-squareds of any of the models in Tables 3 - 7. That being said, the lack of predictive power affects just four asset sectors: Auto Leases and Commercial Mortgages model results differ from the raw data means by 0.02-0.03, while Equipment Leases and Other Consumer Loans differ from the raw data means by only about 0.015.

Pool Yield presents two sectors that differ meaningfully from the raw data means, Equipment Leases (0.0159) and Other Consumer Loans (0.0203). Another sector, Residential Mortgages, differs from the raw means by just 0.0104.

Two Excess Spread sector models differ meaningfully from the raw data means: Auto Leases (0.0117) and Auto Loans (0.0106). Model estimates for all other performance measures and sectors differ from raw data means by less than 0.01.

The correspondence in the mean results in Table 8 is not surprising: the additive effects procedure predicts well because it is implemented over sufficient degrees of freedom that the model forecasts fairly well in the aggregate. Since any possibly significant estimation errors at the pool-month level are averaged across pools in the monthly aggregation, the additive effects procedure maintains the consistency of the aggregate asset class data used to compute the portfolio correlations.

4. Results: Correlations across Credit Types

The coefficients of equation (1) are used to obtain monthly predicted values of the performance measures in each of the pools.[22] The time-series of the mean pool-level monthly performance measures for each asst type are then used to construct the

[22] For parsimony, the monthly least squared mean estimates across the different deals are not reported and are available upon request.

correlations in Tables 9-13. Those correlations are simple Pearson product-moment correlations for each of the performance measures (Pool Yield, 90-day Delinquent Balance, Net Loss Rate, Payment Rate, and Excess Spread, respectively). Sample sizes used to compute the mean performance measures range from 31 to 44 depending upon the availability of time-series data across the asset classes. Table 14 is a summary table of signs and statistical significance of the correlations.

As hoped, the results of the five performance measures for the most part agree. The 390 computed correlations (78 pairwise correlations on five performance measures) yield a total of 178 statistically significant correlation coefficients. Among those statistically significant correlation coefficients, only 19 sign disparities (where the sign of one correlation differs from the rest) occurred among different performance measures among the 78 different asset class combinations.

Disparities are bunched primarily in Excess Spread (10) and Pool Yield (6), with 4 additional disparities in Net Loss Rate (the Manufactured Housing-Equipment Lease correlation has two disparate correlation coefficients). It makes sense that the majority of disparities lie in Excess Spread and Pool Yield: those performance measures have the lowest number of statistically significant correlation coefficients (23 and 27, respectively) and the highest number of negative correlations (13 and 10, respectively). Other sectors have 31 (Net Loss Rate), 47 (Payment Rate) and 48 (90-day Delinquent Balance) statistically significant correlation coefficients with far fewer (5, 0, and 0) negative correlation coefficients.

The disparities are also bunched in particular asset classes. The largest number of disparities are in Auto Leases (7), followed by Equipment Leases (5), Auto Loans (5) and Residential Mortgages (5).[23] Many of these disparities arise because of the fundamental borrower type and the collateral nature of the underlying assets. For instance, Automobile Leases tend to have stable correlations with Equipment Leases, Other Consumer Loans, and Residential Mortgages, and less stable relationships with assets like Credit Cards, Manufactured Housing, and Recreational Vehicle Loans. Auto Loans, on the other hand, seem to cater to a consumer that likes more leverage, having stable correlations with Credit Cards, Marine and Boat Loans, Manufactured Housing, Other Consumer Loans, and Recreational Vehicle Loans, and less stable correlations with Residential Mortgages and Home Equity Loans.

[23] Note that N disparities may affect up to 2*N asset classes. Hence the number of asset classes affected is larger than the number of disparities.

Student Loan correlations are only computed with the 90-day Delinquent Balance performance measure.[24] Not surprisingly, since Student Loans are not dischargeable in consumer bankruptcy, Student Loan 90-day Delinquent Balances are not significantly correlated with any of the other asset classes.

Dealer Floorplans are the next worst-performing category of correlations. Dealer Floorplans are revolving loans made to automobile dealers to finance their inventory on a periodic basis. Dealer Floorplans are not significantly correlated with Automobile Loans, Commercial Mortgages, Marine and Boat Loans, Manufactured Housing, Student Loans, and Home Equity Loans. Dealer Floorplans are, however, the only category to illustrate unchallenged negative correlations with other asset classes. Using the Pool Yield performance measure, Dealer Floorplans are negatively correlated with Automobile Leases, Equipment Leases, Other Consumer Loans, and Residential Mortgages. Dealer Floorplans are also negatively correlated with Residential Mortgages when using Net Loss Rate as the performance measure. The only asset class positively correlated with Dealer Floorplans is Credit Cards.

The highest number of instances of positive correlations exist for Credit Cards and Home Equity Loans. The agreement between Credit Card and Home Equity Loan results is interesting because the two are commonly used interchangeably by consumers. Credit Cards are positively and significantly related to Automobile Loans, Commercial Mortgages, Dealer Floorplans, Marine and Boat Loans, Manufactured Housing, Other Consumer Loans, Recreational Vehicles, and Home Equity Loans. Home Equity Loans only differ in that they are not significantly related to Automobile Loans, but are significantly related to Equipment Leases and Residential Mortgages (the latter because Home Equity Loans are second lien home loans).

Table 15 provides averages of the computed correlations along with the number of performance measures from which they are drawn and a simple standard deviation (to give a sense of the distribution of the estimates in Tables 9-13). A simple coefficient of variation calculation shows that dispersion of the estimated correlations in asset classes where there were disparate signs (CV=2.279) is much greater that that for classes where signs are consistent (CV=0.0295). Hence, Table 15 shades the asset categories for which there is no disparity, as those estimated correlations may be more reliable.

[24] Student Loans are a new, burgeoning asset class, and therefore have relatively little reported data.

The mean correlations in Table 15 from asset classes with no disparity range from a maximum of 0.82 to a minimum of -0.76. The median of all categories with no disparity is 0.50, and the mean is 0.40.

The mean correlations from asset classes with disparity range from a maximum of 0.53 to a minimum of 0.08. The median of the categories with no disparity is 0.329, and the mean is 0.325. Hence, those asset pairs where mean correlations are derived from estimates that exhibit sign disparity exhibit average correlations more closely bunched toward zero, even though none of the correlations are, themselves, on average, negative. In other words, asset pairs that do not exhibit sign disparity exhibit stronger fundamental correlations, positive or negative, than those with sign disparity: they are further away from zero.

What is surprising in the exercise is not that so many asset pairs have sign disparities, and hence exhibit correlations close to zero, but rather how few asset pairs exhibit correlations close to one. After all, the assets are all standard credit products that are largely homogenous and are generally thought to be highly correlated. But with average correlations in Table 15 ranging from 0.82 to -0.76, with a median of 0.42 and a mean of 0.38, there is really quite a bit of room for portfolio diversification.

Appendix E, Tables E1 – E5, shows estimates of the correlations for the performance measures based on Basel II asset categories. Given that there has been some degree of divergent opinion within the Basel community regarding whether Home Equity Loans are more appropriately included with Credit Cards or Residential Mortgages, the analysis examines Residential Mortgages with Home Equity, Residential Mortgages without Home Equity, Other Retail Credit, Qualifying Revolving Credit (Credit Cards), and Home Equity Loans.

The results in Appendix E suggest that Home Equity Loans are more correlated with Qualifying Revolving Credit than with residential Mortgages. Hence, including Home Equity in Residential Mortgages increases the correlation of the Residential Mortgages with the other Basel retail categories (Other Retail and Qualifying Revolving). The implication of that finding is that the ability to achieve portfolio diversification in the forthcoming Basel II regulatory framework is dampened (i.e., banks appear riskier than they may really be) by including Home Equity Loans in the same asset class as Residential Mortgages. That result should appeal to regulators, but not necessarily the banks subject to the new regulatory standards.

Another conclusion to draw from Appendix E is that since nearly all the thirteen categories of loans analyzed above (except, of course, mortgages, home equity, and credit cards) fall into Other Retail Credit, Basel II misses a great deal of diversification benefit (zero, very low, or negative correlations) in those product types. Popular and fast-growing credit sectors like private student loans have very little correlation with other retail credits (presumably because they are not able to be discharged under personal bankruptcy law), a relationship that will benefit bank performance in the next few years, but for which they will receive no credit under Basel II. The reduced ability to discharge credit card debt under the newly revised Federal personal bankruptcy law may result in similar reduced correlations for credit cards. Those low correlations help explain why student loans and credit cards remain two of the fastest-growing asset classes in the banking industry.

5. Conclusions and Extensions

The preceding analysis examined the correlations among different credit products from January 2000 to September 2003. The analysis uses a broad sample of performance measures obtained from $960 billion of asset backed security pools from 524 issuers to derive those asset correlations. Monthly ABS performance data is used to infer asset correlations from several hundred thousand pool-month observations for five different performance measures: Pool Yield, 90-day Delinquent Balance, Net Loss Rate, Payment Rate, and Excess Spread.

Eschewing a bond index approach on the grounds of compositional bias, the analysis relies on an additive effects procedure to estimate a full data panel from which the asset correlations are computed directly. The additive effects procedure explains a large proportion of the variation in the performance measures and does not induce excessive bias or noise into the data process. Asset correlations are estimated using the monthly mean performance values for each asset class. The five 13-asset correlation matrices produced from the different performance measures largely correspond with one another.

The main result of the exercise lies in demonstrating that many credit types, including most retail bank assets, are imperfectly correlated. While the results suggest that there are some systemic short-term economic effects that affect all asset classes in a similar fashion, there does seem to be a significant amount of idiosyncratic risk that is associated with specific asset classes. Since the performance of many different credit types is weakly correlated, and is sometimes even negatively correlated, there is the potential to eliminate a significant amount of risk in retail portfolios of diversified financial institutions.

The conclusions are important for at least three reasons. First, the results suggest that ABS and MBS markets, which currently standing at about $7 trillion of outstanding securities, or about 70% of total consumer debt, may be used to form the basis for analyzing portfolio characteristics of non-traded assets. As the market matures, data such as that used in the present analysis will be used more widely to estimate the portfolio characteristics of a wide variety of non-traded assets.

Second, the ABS and MBS markets are routinely accessed by institutional investors managing pension and mutual funds, and are expected to become even more important to investment managers as the market continues to grow and mature. The present correlations can be used as a foundation for a traditional valuation model by modeling transition probabilities for tranche default within standard ABS structures and then applying the fundamental underlying collateral correlation to the investment after default of junior tranches.

Third, the results show that banks and other financial intermediaries that specialize in retail lending bear less portfolio risk than one might think: bank assets, even among standard credit products, are not perfectly, nor sometimes even closely, correlated with one another, as evidenced by may low, zero, an even negative correlations uncovered in the analysis. Hence, although diversified financial institutions are less risky than monoline or limited-purpose financial institutions, the value of that diversification has not been recognized in Basel II.

The analysis presented above carries many caveats. The correlation estimates are based on credit pools rather than individual loan data. Hence, while we are confident in the statistical applications, much more work will be required before estimates like ours can be used to properly calibrate a practical model like Basel II. We only contend that our analysis points to a new method of calibration for the Basel framework and helps regulators and academics better understand the sources of diversification in opaque portfolios.

Works Cited

Acharya, Viral V., Hasan, Iftekhar and Saunders, Anthony (2006). "Should Banks be Diversified? Evidence from Individual Bank Loan Portfolios" *Journal of Business*, Forthcoming.

Basel Committee on Banking Supervision (2004). *Basel II: International Convergence of Capital Measurement and Capital Standards: a Revised Framework.* Basel, Switzerland: Bank for International Settlements, June.

Bond Market Association. Statistical releases, various issues. http://www.bondmarkets.com/

Calomiris, Charles W., and Joseph R. Mason (2004). "Credit Card Securitization and Regulatory Arbitrage." *Journal of Financial Services Research*, 26, pp. 5-27.

Calomiris, Charles W., and Joseph R. Mason (2006). "Simultaneously Pricing Loans for Default and Prepayment Risk." Working Paper.

Chan, Louis K.C., Jason Karceski, and Josef Lakonishok (1999). "On Portfolio Optimization: Forecasting Covariances and Choosing the Risk Model." *Review of Financial Studies*, 12, pp. 263-78.

Chow, Gregory C., and An-loh Lin (1971). "Best Linear Unbiased Interpolation, Distribution, and Extrapolation of Time Series by Related Series." *Review of Economics and Statistics*, 54, pp. 372-5.

Davidson, R. and J.G. MacKinnon (1993). *Estimation and Inference in Econometrics.* New York: Oxford University Press, pp. 320-323.

Dell'Ariccia, G. and R. Marquez (2004). "Information and Bank Credit Allocation." *Journal of Financial Economics*, 72, pp. 185-214.

Demsetz, Rebecca S. and Philip E. Strahan (1997). "Diversification, Size, and Risk at Bank Holding Companies." *Journal of Money, Credit and Banking* 29, 300-313.

DeYoung, Robert and Karin P. Roland (2001). "Product mix and earnings volatility at commercial banks: Evidence from a degree of total leverage model." *Journal of Financial Intermediation* 10, 54-84.

Elton, E.J. and M.J. Gruber (1973). "Estimating the Dependence Structure of Share Prices – Implications for Portfolio Selection." *Journal of Finance*, 28, pp. 1203-1232.

Elton, Edwin J., Martin J. Gruber, and Jonathan Spitzer (2005). "Improved Estimates of Correlation Coefficients and Their Impact on the Optimum Portfolios." NYU Stern School of Business Working Paper.

Federal Reserve Bank of Philadelphia (2003). "Asset-backed Securities and Credit Cards." Discussion Forum sponsored by the Federal Reserve Bank of Philadelphia, Payment Cards Center, December 2nd and 3rd.

Federal Reserve Statistical Release Z1: Flow of Funds Accounts of the United States. Washington, DC: Board of Governors of the Federal Reserve System, March 10, 2005.

Fitch Research (1996). "ABCs of Credit Card ABS." Structured Finance Special Report, April 1, 1996.

Friedman, Milton (1962). "The Interpolation of Time Series by Related Series." *Journal of the American Statistical Association*, 57, pp. 729-757.

Gorton, Gary B., and George G. Pennacchi (1995). "Bank Loan Sales: Marketing Nonmarketable Assets." *Journal of Monetary Economics*, 35, pp. 389-411.

Higgins, Eric J. and Joseph R. Mason (2004). "What is the Value of Recourse to Asset Backed Securities? A Study of Credit Card Bank ABS Rescues," *Journal of Banking and Finance*, 28, pp. 857-874.

Hirtle, Beverly J. and Kevin J. Stiroh (2005). "The Return to Retail and the Performance of U.S. Banks." Federal Reserve Bank of New York, *Staff Report* 233.

Hughes, Joseph P., William Lang, Loretta J. Mester, Choon-Geol Moon, and Michael Pagano (2003). "Do Bankers Sacrifice Value to Build Empires? Managerial Incentives, Industry Consolidation, and Financial Performance." *Journal of Banking and Finance* 27, 417-447.

Jacob, D.P., L. Graham, and J. A. Tilley (1987). "A Generalized Framework for Pricing Contingent Cash Flows," *Financial Management,* 16, pp. 5-40.

Laeven, Luc and Ross Levine (2006). "Is There a Diversification Discount in Financial Conglomerates? *Journal of Financial Economics*, Forthcoming.

Markowitz, Harry (1952). "Portfolio Selection." *Journal of Finance* 7, pp. 77-91.

Markowitz, Harry (1959). *Portfolio Selection: Efficient Diversification of Investments*. New York: John Wiley & Sons.

Mulvey, J.M. and S.A. Zenios (1994). "Dynamic Diversification of Fixed Income Portfolios," *Financial Analysts Journal*, 50, pp. 30-38.

Nomura Fixed Income Research (2004). *ABS Credit Migrations*.

Securities and Exchange Commission (2004). *Asset-backed Securities*, 17 CFR PARTS 210, 228, 229, 230, 232, 239, 240, 242, 245 and 249, Regulation AB, 33-8518.

Stiroh, Kevin J. and Adrienne Rumble (2005). "The Dark Side of Diversification: The Case of US Financial Holding Companies." *Journal of Banking and Finance*, forthcoming.

Table 1: Average Pool Size for the First Issues Contained Within Sample Period
The following table contains statistics for average pool size from 2000 to September 2003 for the first issue of all asset backed securities grouped according to asset class from the raw data reported by ABSnet. The asset classes available are: Auto Leases, Auto Loans, Credit Cards, Commercial Mortgages, Dealer Floorplan loans, Equipment Leases, Marine and Boat Loans, Manufactured Home loans, Other Consumer loans, Recreational Vehicle loans, Student Loans, Residential Mortgages, and Home Equity Loans. The performance measures examined are average pool size, total income, 90 day delinquent balance percent, Net Loss Rate, Payment Rate, Pool Yield, and Excess Spread.

	Pool Size in $ Millions					
	Number of Issues	Mean	Median	Standard Deviation	Minimum	Maximum
Auto Lease	21	907.072	846.792	641.363	103.206	3005.668
Auto Loans	430	794.445	493.033	871.967	3.526	5907.888
Credit Cards	504	20861.239	15570.909	16996.017	261.131	58187.509
Commercial Mortgages	510	619.945	515.956	619.912	0.262	7793.106
Dealer Floorplans	64	5830.085	5242.738	3353.226	471.978	11523.660
Equipment Leases	113	381.619	312.628	298.725	3.517	1599.134
Marine and Boat	10	160.781	75.985	205.548	6.944	585.236
Manufactured Homes	260	247.949	161.668	291.895	4.915	2458.612
Other Consumer Loans	43	993.922	295.553	2927.086	22.847	19039.386
Recreational Vehicles	30	235.625	125.399	229.005	17.143	814.658
Student Loans	49	1250.112	1214.387	687.659	30.418	2505.477
Residential Mortgages	1673	618.687	166.114	2519.424	0.178	24026.953
Home Equity Loans	2559	248.551	143.797	390.107	0.311	10174.060

Table 2: Median Performance Measures by Asset Class from Raw Data

The following table contains median monthly performance measures from January 2000 to September 2003 for asset backed securities grouped according to asset class from the raw data reported by ABSnet. The asset classes available are: Auto Leases, Auto Loans, Credit Cards, Commercial Mortgages, Dealer Floorplan loans, Equipment Leases, Marine and Boat Loans, Manufactured Home loans, Other Consumer loans, Recreational Vehicle loans, Student Loans, Residential Mortgages, and Home Equity Loans. The performance measures examined are average pool size, total income, 90 day delinquent balance percent, Net Loss Rate, Payment Rate, Pool Yield, and Excess Spread.

	Median Performance Measure with Sample Size in ( )					
	Avg. Pool size (in $ millions)	Pool Yield	90 - Day Delinquent Percent	Net Loss Rate	Payment Rate	Excess Spread
Auto Lease	649.54 (357)	0.1053 (319)	0.0057 (286)	0.0034 (268)	0.0352 (332)	0.0383 (280)
Auto Loans	292.44 (9018)	0.1093 (8281)	0.0026 (6808)	0.0189 (8727)	0.0437 (8277)	0.0163 (8177)
Credit Cards	21647.28 (14159)	0.1884 (14463)	0.0123 (12021)	0.0567 (11932)	0.1430 (14416)	0.0617 (14045)
Commercial Mortgages	676.55 (11253)	0.0769 (87)	0.0000 (11072)	0.0000 (231)	0.0341 (263)	0.0102 (22)
Dealer Floorplans	5025.53 (1520)	0.0736 (1437)	0.0016 (9)	0.0000 (607)	0.4220 (1535)	0.0215 (1254)
Equipment Leases	169.97 (2532)	0.1011 (498)	0.0092 (1627)	0.0052 (1913)	0.0640 (580)	0.0161 (274)
Marine and Boat	56.28 (362)	0.1013 (362)	0.0040 (363)	0.0092 (362)	0.0273 (361)	0.0159 (361)
Manufactured Homes	144.89 (9313)	0.1026 (7956)	0.0144 (7819)	0.0247 (7492)	0.0088 (9157)	0.0009 (7835)
Other Consumer Loans	100.50 (867)	0.2264 (714)	0.0095 (782)	0.0176 (285)	0.0297 (699)	0.2001 (561)
Recreational Vehicles	73.36 (1036)	0.0946 (1035)	0.0030 (1014)	0.0130 (1023)	0.0245 (1035)	0.0102 (1034)
Student Loans	1046.57 (395)	0.0654 (385)	0.0104 (133)	0.0004 (218)	0.0499 (361)	0.0291 (376)
Residential Mortgages	68.71 (46585)	0.0724 (4470)	0.0003 (46585)	0.0000 (32747)	0.0359 (29092)	0.0024 (3145)
Home Equity Loans	67.12 (75958)	0.1004 (24801)	0.0124 (60039)	0.0059 (66044)	0.0257 (61036)	0.0184 (22959)

Table 3: Estimation of Variation in Pool Yield

The following table reports the results of the estimation of equation (1) *Y=f(pool, time)* for each asset class where *Y* is the Pool Yield. To be included in the analysis a pool must have at least six valid observations for Pool Yield over the January 2000 to September 2003 time period. Extreme observations are eliminated from the analysis. N.E. indicates that the model was not estimable due to a lack of observations either over time or across pools. An asterisk indicates significance at the 5% level.

		Source of Variation in Yield with F-statistic Testing Significance		
Asset class	N	Pool	Time	Model R-squared
Auto Lease	294	10.94*	1.49*	0.4982
Auto Loans	8097	34.40*	2.19*	0.6091
Credit Cards	9022	158.28*	74.40*	0.8695
Commercial Mortgages	63	5.67*	1.52	0.7815
Dealer Floorplans	1032	101.18*	24.77*	0.8683
Equipment Leases	463	44.84*	1.01	0.7074
Marine and Boat	362	73.63*	1.65*	0.7191
Manufactured Homes	7885	91.53*	5.77*	0.7239
Other Consumer	612	95.57*	3.06*	0.8097
Recreational Vehicles	1035	27.97*	1.24	0.4747
Student Loans	N.E.	N.E.	N.E.	N.E.
Residential Mortgages	4028	51.55*	3.13*	0.7411
Home Equity Loans	23758	38.35*	5.49*	0.5890

Table 4: Estimation of Variation in 90-day Delinquent Balance

The following table reports the results of the estimation of equation (1) *Y=f(pool, time)* for each asset class where *Y* is the 90-day Delinquent Balance. To be included in the analysis a pool must have at least six valid observations for 90-day Delinquent Balance over the January 2000 to September 2003 time period. Extreme observations are eliminated from the analysis. N.E. indicates that the model was not estimable due to a lack of observations either over time or across pools. An asterisk indicates significance at the 5% level.

		Source of Variation with F-statistic Testing Significance		
Asset class	N	Pool	Time	Model R-squared
Auto Lease	283	14.74*	2.53*	0.5279
Auto Loans	6688	48.52*	36.46*	0.6823
Credit Cards	7282	700.56*	29.35*	0.9659
Commercial Mortgages	6766	49.50*	6.65*	0.6013
Dealer Floorplans	N.E.	N.E.	N.E.	N.E.
Equipment Leases	1612	36.59*	4.18*	0.6229
Marine and Boat	344	257.58*	1.45*	0.8857
Manufactured Homes	7800	148.33*	23.18*	0.8207
Other Consumer	655	91.19*	0.92	0.7726
Recreational Vehicles	1014	80.68*	2.87*	0.7186
Student Loans	82	74.67*	1.85*	0.9680
Residential Mortgages	36940	51.32*	14.94*	0.6620
Home Equity Loans	58895	126.71*	55.57*	0.8040

Table 5: Estimation of Variation in Net Loss Rate

The following table reports the results of the estimation of equation (1) *Y=f(pool, time)* for each asset class where *Y* is the Net Loss Rate. To be included in the analysis a pool must have at least six valid observations for Net Loss Rate over the January 2000 to September 2003 time period. Extreme observations are eliminated from the analysis. N.E. indicates that the model was not estimable due to a lack of observations either over time or across pools. An asterisk indicates significance at the 5% level.

		Source of Variation with F-statistic Testing Significance		
Asset class	N	Pool	Time	Model R-squared
Auto Lease	264	7.55*	1.11	0.4265
Auto Loans	8561	27.42*	19.16*	0.5464
Credit Cards	7676	209.82*	34.33*	0.9002
Commercial Mortgages	130	1.67	0.85	0.3782
Dealer Floorplans	511	6.62*	1.10	0.2741
Equipment Leases	1838	5.82*	0.97	0.2154
Marine and Boat	362	8.48*	1.63*	0.3209
Manufactured Homes	7234	16.25*	69.91*	0.4751
Other Consumer	244	19.55*	0.84	0.5646
Recreational Vehicles	1023	35.92*	2.13*	0.5547
Student Loans	N.E.	N.E.	N.E.	N.E.
Residential Mortgages	22088	47.83*	3.51*	0.6103
Home Equity Loans	61037	19.00*	15.97*	0.3860

Table 6: Estimation of Variation in Payment Rate

The following table reports the results of the estimation of equation (1) *Y=f(pool, time)* for each asset class where *Y* is the Payment Rate. To be included in the analysis a pool must have at least six valid observations for Payment Rate over the January 2000 to September 2003 time period. Extreme observations are eliminated from the analysis. N.E. indicates that the model was not estimable due to a lack of observations either over time or across pools. An asterisk indicates significance at the 5% level.

		Source of Variation with F-statistic Testing Significance		
Asset class	N	Pool	Time	Model R-squared
Auto Lease	329	10.88*	2.53*	0.4742
Auto Loans	8098	7.66*	15.78*	0.2558
Credit Cards	8980	2232.96*	47.77*	0.9891
Commercial Mortgages	241	4.90*	3.01*	0.5464
Dealer Floorplans	1130	92.67*	44.48*	0.8482
Equipment Leases	557	3.00*	3.53*	0.2763
Marine and Boat	361	7.42*	7.56*	0.5573
Manufactured Homes	9109	6.18*	2.27*	0.1513
Other Consumer	618	12.28*	1.08	0.3682
Recreational Vehicles	1034	1.76*	1.34	0.0903
Student Loans	N.E.	N.E.	N.E.	N.E.
Residential Mortgages	27880	5.89*	116.21*	0.2914
Home Equity Loans	60182	13.01*	44.17*	0.3186

Table 7: Estimation of Variation in Excess Spread

The following table reports the results of the estimation of equation (1) *Y=f(pool, time)* for each asset class where *Y* is the Excess Spread. To be included in the analysis a pool must have at least six valid observations for Excess Spread over the January 2000 to September 2003 time period. Extreme observations are eliminated from the analysis. N.E. indicates that the model was not estimable due to a lack of observations either over time or across pools. An asterisk indicates significance at the 5% level.

		Source of Variation with F-statistic Testing Significance		
Asset class	N	Pool	Time	Model R-squared
Auto Lease	252	11.99*	1.58*	0.5255
Auto Loans	7993	22.18*	14.85*	0.5087
Credit Cards	13078	60.43*	29.34*	0.6947
Commercial Mortgages	N.E.	N.E.	N.E.	N.E.
Dealer Floorplans	1238	40.03*	2.45*	0.6585
Equipment Leases	251	33.74*	2.21*	0.7117
Marine and Boat	361	8.16*	2.09*	0.3623
Manufactured Homes	7781	58.44*	46.81*	0.6488
Other Consumer	550	99.26*	2.14*	0.7909
Recreational Vehicles	1034	25.85*	1.94*	0.4785
Student Loans	N.E.	N.E.	N.E.	N.E.
Residential Mortgages	2779	54.95*	1.26	0.7544
Home Equity Loans	22339	36.46*	4.25*	0.5733

Table 8: Mean Performance Measures by Asset Class from Screened Data and Model Estimates

The following table contains mean monthly performance measures from January 2000 to September 2003 for asset backed securities grouped according to asset class for data from ABSnet that has been screened for extreme observations, missing observations, and repeated observations. The table also contains mean values for performance measures for each asset class based on estimates from equation (1), *Y=f(pool, time)*, for each asset class. N.A. indicates that the variable was unavailable. N.E. indicates that the model was not estimable due to a lack of observations either over time or across pools.

	Pool Yield	90 - Day Delinquent Percent	Net Loss Rate	Payment Rate	Excess Spread
	Mean Values from Screened Data and (Model Estimation)				
Auto Lease	0.1690 (0.1653)	0.0008 (0.0008)	0.0056 (0.0060)	0.0604 (0.0346)	0.0951 (0.1068)
Auto Loans	0.1197 (0.1209)	0.0063 (0.0056)	0.0325 (0.0276)	0.0616 (0.0622)	0.0179 (0.0285)
Credit Cards	0.2029 (0.2037)	0.0157 (0.0158)	0.0638 (0.0639)	0.1611 (0.1638)	0.0698 (0.0729)
Commercial Mortgages	0.0766 (0.0738)	0.0092 (0.0102)	0.0006 (0.0003)	0.0683 (0.0905)	N.A. (N.E.)
Dealer Floorplans	0.0750 (0.0763)	0.0021 (N.E.)	0.0009 (0.0007)	0.4143 (0.4146)	0.0211 (0.0210)
Equipment Leases	0.1385 (0.1544)	0.0149 (0.0127)	0.0137 (0.0097)	0.0799 (0.0983)	0.0512 (0.0583)
Marine and Boat	0.1004 (0.1015)	0.0060 (0.0079)	0.0132 (0.0138)	0.0289 (0.0287)	0.0161 (0.0157)
Manufactured Homes	0.1074 (0.1106)	0.0209 (0.0181)	0.0362 (0.0349)	0.0119 (0.0146)	-0.0011 (0.0012)
Other Consumer	0.2507 (0.2277)	0.0111 (0.0110)	0.0219 (0.0152)	0.0357 (0.0491)	0.1819 (0.1896)
Recreational Vehicles	0.0999 (0.1042)	0.0043 (0.0048)	0.0193 (0.0199)	0.0322 (0.0354)	0.0098 (0.0148)
Student Loans	0.0652 (N.E.)	0.0169 (0.0186)	0.0004 (N.E.)	0.0555 (N.E.)	0.0272 (N.E.)
Residential Mortgages	0.0816 (0.0712)	0.0075 (0.0086)	0.0044 (0.0054)	0.0589 (0.0516)	0.0266 (0.0207)
Home Equity Loans	0.1056 (0.1054)	0.0411 (0.0352)	0.0251 (0.0202)	0.0355 (0.0319)	0.0218 (0.0275)

Table 9: Estimation of Pool Yield Correlations across Asset classes

The following table contains the Pearson product-moment correlation of Pool Yields across asset classes. The following abbreviations for asset classes are used: ALoan = Auto Loans, ALease = Auto Leases, CMBS = Commercial Mortgage Loans, CC = Credit Card Receivables, DFP = Dealer Floorplan Loans, ELease = Equipment Leases, MB = Marine and Boat Loans, MH = Manufactured Home Loans, OCL = Other Consumer Loans, RV = Recreational Vehicle Loans, Student = Student Loans, RMBS = Residential Mortgage Loans, HEL = Home Equity Loans. To be included in the sample a particular pool must have at least six observations within the January 2000 to September 2003 time period. Extreme values for Pool Yield are not included in the analysis. Monthly mean values over the time period from January 2000 to September 2003 for Pool Yield are obtained by finding the least squared mean values. Least squared mean values are found by estimating equation (1), *Y=f(pool, time).* An asterisk indicates that the correlation is significantly different from zero at the 5% level. N.A. indicates that the particular asset class was not available for study due to lack of sufficient observations.

	ALoan	ALease	CMBS	CC	DFP	ELease	MB	MH	OCL	RV	Student	RMBS	HEL
ALoan	1.0000												
ALease	0.1598	1.0000											
CMBS	0.1114	0.0554	1.0000										
CC	-0.1537	-0.7909*	0.0523	1.0000									
DFP	-0.1029	-0.7644*	0.1885	0.7335*	1.0000								
ELease	0.3461*	0.5695*	-0.0759	-.04796*	-0.6677*	1.0000							
MB	0.4453*	-0.1422	0.0648	0.3133*	0.0896	-0.0687	1.0000						
MH	0.2092	-0.1829	0.0038	0.2831*	0.2597	-0.0458	0.1779	1.0000					
OCL	0.2739*	0.3101*	0.1671	-0.2448	-0.3495*	0.3222*	0.0299	-0.1499	1.0000				
RV	0.3739*	-0.1897	0.0943	0.0574	0.0367	0.0473	0.3154*	-0.1279	0.2771*	1.0000			
Student	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	1.0000		
RMBS	0.1535	0.5118*	-0.3727*	-0.5217*	-0.7161*	0.476*	-0.0805	-0.2739*	0.0699	0.1253	N.A.	1.0000	
HEL	0.3529*	-.03965*	-0.0416	-0.0870	0.5198	-0.1106	0.3102*	0.4011*	-0.1279	0.1033	N.A.	-0.0920	1.0000

Table 10: Estimation of 90-day Delinquent Balance Correlations across Asset classes

The following table contains the Pearson product-moment correlation of 90-day Delinquent Balances across asset classes. The following abbreviations for asset classes are used: ALoan = Auto Loans, ALease = Auto Leases, CMBS = Commercial Mortgage Loans, CC = Credit Card Receivables, DFP = Dealer Floorplan Loans, ELease = Equipment Leases, MB = Marine and Boat Loans, MH = Manufactured Home Loans, OCL = Other Consumer Loans, RV = Recreational Vehicle Loans, Student = Student Loans, RMBS = Residential Mortgage Loans, HEL = Home Equity Loans. To be included in the sample a particular pool must have at least six observations within the January 2000 to September 2003 time period. Extreme values for 90-day Delinquent Balance are not included in the analysis. Monthly mean values over the time period from January 2000 to September 2003 for 90-day Delinquent Balance are obtained by finding the least squared mean values. Least squared mean values are found by estimating equation (1), *Y=f(pool, time)*. An asterisk indicates that the correlation is significantly different from zero at the 5% level. N.A. indicates that the particular asset class was not available for study due to lack of sufficient observations.

	ALoan	ALease	CMBS	CC	DFP	ELease	MB	MH	OCL	RV	Student	RMBS	HEL
ALoan	1.0000												
ALease	0.8533*	1.0000											
CMBS	0.9373*	0.8553*	1.0000										
CC	0.6810*	0.5927*	0.6293*	1.0000									
DFP	N.A.	N.A.	N.A.	N.A.	1.0000								
ELease	0.8293*	0.8508*	0.8463*	0.6230*	N.A.	1.0000							
MB	0.3451*	0.4196*	0.2421	0.3123*	N.A.	0.1870	1.0000						
MH	0.8856*	0.7459*	0.7943*	0.7407*	N.A.	0.7097*	0.3823*	1.0000					
OCL	0.2605*	0.1751	0.2163	0.4682*	N.A.	0.1885	0.1848	0.2854*	1.0000				
RV	0.6657*	0.5864*	0.6540*	0.3916*	N.A.	0.6017*	0.2697*	0.6519*	0.3697*	1.0000			
Student	0.1036	-0.1156	0.0854	0.2245	N.A.	0.0343	-0.1492	0.2925	-0.0743	0.1053	1.0000		
RMBS	0.9181*	0.7339*	0.8539*	0.6459*	N.A.	0.6590*	0.3182*	0.8308*	0.3010*	0.6072*	0.0589	1.0000	
HEL	0.9677*	0.8429*	0.9478*	0.6449*	N.A.	0.8702*	0.2663*	0.8074*	0.2318	0.6131*	0.0675	0.8888*	1.0000

Table 11: Estimation of Net Loss Rate Correlations across Asset classes

The following table contains the Pearson product-moment correlation of Net Loss Rates across asset classes. The following abbreviations for asset classes are used: ALoan = Auto Loans, ALease = Auto Leases, CMBS = Commercial Mortgage Loans, CC = Credit Card Receivables, DFP = Dealer Floorplan Loans, ELease = Equipment Leases, MB = Marine and Boat Loans, MH = Manufactured Home Loans, OCL = Other Consumer Loans, RV = Recreational Vehicle Loans, Student = Student Loans, RMBS = Residential Mortgage Loans, HEL = Home Equity Loans. To be included in the sample a particular pool must have at least six observations within the January 2000 to September 2003 time period. Extreme values for Net Loss Rate are not included in the analysis. Monthly mean values over the time period from January 2000 to September 2003 for Net Loss Rate are obtained by finding the least squared mean values. Least squared mean values are found by estimating equation (1), *Y=f(pool, time)*. An asterisk indicates that the correlation is significantly different from zero at the 5% level. N.A. indicates that the particular asset class was not available for study due to lack of sufficient observations.

	ALoan	ALease	CMBS	CC	DFP	ELease	MB	MH	OCL	RV	Student	RMBS	HEL
ALoan	1.0000												
ALease	0.4561*	1.0000											
CMBS	-0.0079*	-0.1078*	1.0000										
CC	0.7899*	0.4120*	-0.0722	1.0000									
DFP	-0.1694	0.0410	0.0467	-0.1401	1.0000								
ELease	-0.2464	0.0501	-0.0967	0.0780	0.1174	1.0000							
MB	0.1593	0.2848*	-0.0580	0.1076	0.0313	-0.2533*	1.0000						
MH	0.8769*	0.3635*	-0.0365	0.7768*	-0.2539	-0.2550*	0.1063	1.0000					
OCL	0.4518*	0.2061	0.0023	0.3618*	0.0597	0.1339	0.1022	0.4130*	1.0000				
RV	0.7447*	0.2014	-0.0846	0.6731*	-0.1289	0.1576	0.1877	0.7549*	0.3527*	1.0000			
Student	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	1.0000		
RMBS	0.3800*	0.1906	0.0339	0.3748*	-0.3309*	0.0725	0.0062	0.5447*	0.0204	0.4475*	N.A.	1.0000	
HEL	0.5513*	0.4508*	0.0298	0.7429*	-0.2294	0.4403*	0.1064	0.6006*	0.5160*	0.6987*	N.A.	0.3972*	1.0000

Table 12: Estimation of Pool Payment Rate Correlations across Asset classes
The following table contains the Pearson product-moment correlation of Payment Rates across asset classes. The following abbreviations for asset classes are used: ALoan = Auto Loans, ALease = Auto Leases, CMBS = Commercial Mortgage Loans, CC = Credit Card Receivables, DFP = Dealer Floorplan Loans, ELease = Equipment Leases, MB = Marine and Boat Loans, MH = Manufactured Home Loans, OCL = Other Consumer Loans, RV = Recreational Vehicle Loans, Student = Student Loans, RMBS = Residential Mortgage Loans, HEL = Home Equity Loans. To be included in the sample a particular pool must have at least six observations within the January 2000 to September 2003 time period. Extreme values for Payment Rate are not included in the analysis. Monthly mean values over the time period from January 2000 to September 2003 for Payment Rate are obtained by finding the least squared mean values. Least squared mean values are found by estimating equation (1), *Y=f(pool, time)*. An asterisk indicates that the correlation is significantly different from zero at the 5% level. N.A. indicates that the particular asset class was not available for study due to lack of sufficient observations.

	ALoan	ALease	CMBS	CC	DFP	ELease	MB	MH	OCL	RV	Student	RMBS	HEL
ALoan	1.0000												
ALease	0.7775*	1.0000											
CMBS	0.6648*	0.8180*	1.0000										
CC	0.5097*	0.4321*	0.3069*	1.0000									
DFP	0.0793	-0.2485	-0.2483	0.3251*	1.0000								
ELease	0.7129*	0.7505*	0.5942*	0.3376*	-0.0876	1.0000							
MB	0.6006*	0.6289*	0.5643*	0.4648*	0.0894	0.4171*	1.0000						
MH	0.6090*	0.3345*	0.3032*	0.1639	0.0232	0.4591*	0.1818	1.0000					
OCL	0.2631*	0.2123	0.2428	0.2217	0.0766	0.1313	0.3069*	0.0183	1.0000				
RV	0.6489*	0.6238*	0.4424*	0.4315	-0.0156	0.5652*	0.4218*	0.3655*	0.0951	1.0000			
Student	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	1.0000		
RMBS	0.8171*	0.9280*	0.8025*	0.4942*	-0.2085	0.7648*	0.6291*	0.4101*	0.2516*	0.6868*	N.A.	1.0000	
HEL	0.5854*	0.8706*	0.6945*	0.3821*	-0.0578	0.7754*	0.6646*	0.3095*	0.2194*	0.6359*	N.A.	0.7675*	1.0000

Table 13: Estimation of Excess Spread Correlations across Asset classes

The following table contains the Pearson product-moment correlation of Excess Spreads across asset classes. The following abbreviations for asset classes are used: ALoan = Auto Loans, ALease = Auto Leases, CMBS = Commercial Mortgage Loans, CC = Credit Card Receivables, DFP = Dealer Floorplan Loans, ELease = Equipment Leases, MB = Marine and Boat Loans, MH = Manufactured Home Loans, OCL = Other Consumer Loans, RV = Recreational Vehicle Loans, Student = Student Loans, RMBS = Residential Mortgage Loans, HEL = Home Equity Loans. To be included in the sample a particular pool must have at least six observations within the January 2000 to September 2003 time period. Extreme values for Excess Spread are not included in the analysis. Monthly mean values over the time period from January 2000 to September 2003 for Excess Spread are obtained by finding the least squared mean values. Least squared mean values are found by estimating equation (1), *Y=f(pool, time)*. An asterisk indicates that the correlation is significantly different from zero at the 5% level. N.A. indicates that the particular asset class was not available for study due to lack of sufficient observations.

	ALoan	ALease	CMBS	CC	DFP	ELease	MB	MH	OCL	RV	Student	RMBS	HEL
ALoan	1.0000												
ALease	-0.7717*	1.0000											
CMBS	N.A.	N.A.	1.0000										
CC	-0.1378	0.0975	N.A.	1.0000									
DFP	-0.0364	0.0335	N.A.	-0.0702	1.0000								
ELease	-0.6068*	0.6780*	N.A.	0.5623*	-0.1093	1.0000							
MB	0.3458*	-0.2880*	N.A.	-0.0106	0.0020	-0.1518	1.0000						
MH	0.8591*	-0.7607*	N.A.	0.1304	0.0335	-0.5697*	0.1669	1.0000					
OCL	-0.1376	0.3369*	N.A.	0.1787	-0.2464	0.3069*	0.3957*	-0.2434	1.0000				
RV	0.6896*	-0.5890*	N.A.	-0.0245	0.0616	-0.3501*	0.2511	0.6390*	-0.1290	1.0000			
Student	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	1.0000		
RMBS	-0.2835*	0.2506	N.A.	0.3112*	-0.0807	0.4482*	-0.0874	-0.1164	0.1839	-0.2834*	N.A.	1.0000	
HEL	-0.2817*	0.1372	N.A.	0.3467*	-0.0545	0.4038*	-0.0235	-0.2395	0.0887	-0.0514	N.A.	0.0764	1.0000

Table 14: Summary of Signs and Significance for Performance Correlations

The following table represents signs and statistical significance of correlations computed from each of the performance measures. The following abbreviations for asset classes are used: ALoan = Auto Loans, ALease = Auto Leases, CMBS = Commercial Mortgage Loans, CC = Credit Card Receivables, DFP = Dealer Floorplan Loans, ELease = Equipment Leases, MB = Marine and Boat Loans, MH = Manufactured Home Loans, OCL = Other Consumer Loans, RV = Recreational Vehicle Loans, Student = Student Loans, RMBS = Residential Mortgage Loans, HEL = Home Equity Loans. Symbols in the table indicate sign and significance of the correlations: 0=statistically insignificant, 1=positive and statistically significant, -1=negative and statistically significant, NA=not available. Performance measures in each cell are in order as Pool Yield, 90-day Delinquent Balance, Net Loss Rate, Payment Rate, and Excess Spread, respectively. Cells are shaded to indicate that there exists no sign disparity across statistically significant correlations among the performance measures. Unshaded cells are those in which signs of statistically significant correlations disagreed for one or more performance measure. Cells with no significant correlation coefficients are deemphasized in gray text.

	ALoan	ALease	CMBS	CC	DFP	ELease	MB	MH	OCL	RV	Student	RMBS	HEL
ALoan	, , , ,												
ALease	0, 1, 1, 1, -1	, , , ,											
CMBS	0, 1, -1, 1, NA	0, 1, -1, 1, NA	, , , ,										
CC	0, 1, 1, 1, 0	-1, 1, 1, 1, 0	0, 1, 0, 1, NA	, , , ,									
DFP	0, NA, 0, 0, 0	-1, NA, 0, 0, 0	0, NA, 0, 0, NA	1, NA, 0, 1, 0	, , , ,								
ELease	1, 1, 0, 1, -1	1, 1, 0, 1, 1	0, 1, 0, 1, NA	-1, 1, 0, 1, 1	-1, NA, 0, 0, 0	, , , ,							
MB	1, 1, 0, 1, 1	0, 1, 1, 1, -1	0, 0, 0, 1, NA	1, 1, 0, 1, 0	0, NA, 0, 0, 0	0, 0, -1, 1, 0	, , , ,						
MH	0, 1, 1, 1, 1	0, 1, 1, 1, -1	0, 1, 0, 1, NA	1, 1, 1, 0, 0	0, NA, 0, 0, 0	0, 1, -1, 1, -1	0, 1, 0, 0, 0	, , , ,					
OCL	1, 1, 1, 1, 0	1, 0, 0, 0, 1	0, 0, 0, 0, NA	0, 1, 1, 0, 0	-1, NA, 0, 0, 0	1, 0, 0, 0, 1	0, 0, 0, 1, 1	0, 1, 1, 0, 0	, , , ,				
RV	1, 1, 1, 1, 1	0, 1, 0, 1, -1	0, 1, 0, 1, NA	0, 1, 1, 0, 0	0, NA, 0, 0, 0	0, 1, 0, 1, -1	1, 1, 0, 1, 0	0, 1, 1, 1, 1	1, 1, 1, 0, 0	, , , ,			
Student	NA, 0, NA, NA, NA	NA, 0, NA, NA, NA	NA, 0, NA, NA, NA	NA, 0, NA, NA, NA	NA, NA, NA, NA, NA	NA, 0, NA, NA, NA	NA, 0, NA, NA, NA	NA, 0, NA, NA, NA	NA, 0, NA, NA, NA	NA, 0, NA, NA, NA	, , , ,		
RMBS	0, 1, 1, 1, -1	1, 1, 0, 1, 0	-1, 1, 0, 1, NA	-1, 1, 1, 1, 1	-1, NA, -1, 0, 0	1, 1, 0, 1, 1	0, 1, 0, 1, 0	-1, 1, 1, 1, 0	0, 1, 0, 1, 0	0, 1, 1, 1, -1	NA, 0, NA, NA, NA	, , , ,	
HEL	1, 1, 1, 1, -1	-1, 1, 1, 1, 0	0, 1, 0, 1, NA	0, 1, 1, 1, 1	0, NA, 0, 0, 0	0, 1, 1, 1, 1	1, 1, 0, 1, 0	1, 1, 1, 1, 0	0, 0, 1, 1, 0	0, 1, 1, 1, 0	NA, 0, NA, NA, NA	0, 1, 1, 1, 0	, , , ,

Table 15: Average Correlation Coefficients across Performance Measures

The following table presents the averages of the statistically significant correlation coefficients for the different performance measures (in bold), the number of performance measures the average is derived from, and the standard deviation (in italic) among those correlation coefficients. The following abbreviations for asset classes are used: ALoan = Auto Loans, ALease = Auto Leases, CMBS = Commercial Mortgage Loans, CC = Credit Card Receivables, DFP = Dealer Floorplan Loans, ELease = Equipment Leases, MB = Marine and Boat Loans, MH = Manufactured Home Loans, OCL = Other Consumer Loans, RV = Recreational Vehicle Loans, Student = Student Loans, RMBS = Residential Mortgage Loans, HEL = Home Equity Loans. Cells are shaded to indicate that there exists no sign disparity across statistically significant correlations among the performance measures. Unshaded cells are those in which signs of statistically significant correlations disagreed for one or more performance measure. Cells with correlation coefficients that statistically insignificantly different from zero are blank (meaning a comparison is not necessary).

	ALoan	ALease	CMBS	CC	DFP	ELease	MB	MH	OCL	RV	Student	RMBS	HEL
ALoan	1												
ALease	**0.329** 4 *0.754*	1											
CMBS	**0.531** 3 *0.487*	**0.522** 3 *0.546*	1										
CC	**0.660** 3 *0.141*	**0.161** 4 *0.640*	**0.468** 2 *0.228*	1									
DFP	0.000	**-0.764** 1 *N.A.*	0.000	**0.529** 2 *0.289*	1								
ELease	**0.320** 4 *0.652*	**0.712** 4 *0.119*	**0.720** 2 *0.178*	**0.369** 4 *0.304*	**-0.668** 1 *N.A.*	1							
MB	**0.434** 4 *0.121*	**0.261** 4 *0.393*	**0.564** 1 *N.A.*	**0.363** 3 *0.088*	0.000	**0.082** 2 *0.474*	1						
MH	**0.808** 4 *0.133*	**0.171** 4 *0.649*	**0.549** 2 *0.347*	**0.600** 3 *0.275*	0.000	**0.086** 4 *0.598*	**0.382** 1 *N.A.*	1					
OCL	**0.312** 4 *0.093*	**0.324** 2 *0.019*	0.000	**0.415** 2 *0.075*	**-0.350** 1 *N.A.*	**0.315** 2 *0.011*	**0.351** 2 *0.063*	**0.349** 2 *0.090*	1				
RV	**0.625** 5 *0.145*	**0.207** 3 *0.690*	**0.548** 2 *0.150*	**0.532** 2 *0.199*	0.000	**0.272** 3 *0.539*	**0.336** 3 *0.078*	**0.603** 4 *0.167*	**0.333** 3 *0.049*	1			
Student	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1		
RMBS	**0.458** 4 *0.547*	**0.725** 3 *0.208*	**0.428** 3 *0.694*	**0.261** 5 *0.456*	**-0.524** 2 *0.272*	**0.587** 4 *0.151*	**0.474** 2 *0.220*	**0.378** 4 *0.469*	**0.276** 2 *0.035*	**0.365** 4 *0.443*	0.000	1	
HEL	**0.435** 5 *0.458*	**0.531** 4 *0.426*	**0.821** 2 *0.179*	**0.529** 4 *0.195*	0.000	**0.622** 4 *0.235*	**0.414** 3 *0.218*	**0.530** 4 *0.221*	**0.368** 2 *0.210*	**0.649** 3 *0.044*	0.000	**0.685** 3 *0.256*	1

Appendix A: Issuers in ABS and MBS Sample Sectors

Sector	Name	Maximum Outstanding
Auto Leases	BMW	1,547,538,089
	Chesapeake Funding LLC	887,694,509
	FACT Limited	379,242,755
	Ford Credit	109,922,431
	Honda Auto	3,026,534,485
	MMCA	901,698,217
	NIF-T (Nissan Canada)	416,138,127
	Nissan Auto	1,317,429,440
	Rental Car Finance Corp.	350,000,000
	Toyota Auto	1,017,929,711
	VCL Ltd.	1,000,000,000
	Volkswagen Auto	1,630,434,783
	World Omni	868,519,024
Auto Loans	Advanta	10,774,953
	AFG Receivables	31,672,759
	AmeriCredit	1,857,924,722
	AmSouth	950,415,639
	ANRC	786,800,000
	Arcadia	578,470,196
	Associates	833,347,584
	Auto ABS Compartment	1,500,029,948
	Banc One	235,062,623
	Barnett	221,941,759
	Bay View	453,210,907
	BMW	1,643,640,298
	Boatmens	21,589,405
	Capital Auto Receivables	3,850,059,521
	Capital One Auto Finance	1,265,040,000
	Carmax	641,725,018
	Chase Manhattan	2,024,000,000
	Chevy Chase	403,332,000
	Compass	151,709,572
	Conseco Finance	609,410,972
	Continental	155,261,472
	Credit Acceptance	553,385,924
	DaimlerChrysler	2,400,004,065
	Dealer Auto Receivables	752,896,592
	Drive Auto Receivables	222,804,267
	FASCO	11,667,549
	Fifth Third Bank	31,412,745
	First Security	1,510,930,000
	First Tennessee	189,999,708
	Ford Credit	5,999,999,848
	Franklin	318,020,001
	Globaldrive B.V.	800,000,000

	GMAC	200,731,637
	GS Auto Loan	527,442,161
	Home Federal	50,001,870
	Honda Auto	2,082,211,928
	Household	1,489,361,729
	Huntington	481,740,285
	Hyundai Auto	800,000,008
	Isuzu Auto	432,739,785
	Key Auto	421,314,009
	Long Beach Acceptance	250,000,000
	M&I Auto	432,770,484
	Mellon	351,261,292
	MMCA Auto	1,691,514,913
	National Auto Finance	9,302,630
	National City	1,110,594,101
	NationsBank	177,215,574
	New South	125,991,300
	Nissan Auto	1,705,237,150
	Norwest	68,372,335
	Olympic	249,680,227
	Onyx Acceptance	450,000,000
	Paragon	76,043,412
	PeopleFirst.Com	534,351,145
	Premier Auto	1,465,816,609
	Prestige Auto	96,336,263
	Regions Auto	800,000,001
	SSB Auto	658,929,999
	Summit Acceptance Corporation, LLC	129,666,767
	The Money Store	31,372,816
	Toyota Auto	1,600,001,788
	Tranex Auto	13,330,036
	Triad Auto	983,332,517
	UACSC Auto	815,537,314
	United Fidelity	36,000,535
	USAA	1,830,145,725
	Wells Fargo	746,594,524
	WFS Financial	1,800,000,000
	Whole Auto Loan	3,000,003,566
	Windsor	480,003,183
Credit Cards	Advanta	2,735,160,079
	American Express	22,822,161,295
	Associates	5,872,467,834
	Bank of America	9,629,336,872
	Banc One	7,402,113,611
	Bridgestone/Firestone	337,435,534
	Cabela's	627,315,543
	Canadian	1,254,704,556
	Canadian Tire	1,559,050,686
	Capital One	26,837,278,188

	Charming Shoppes	284,202,832
	Chase	33,353,331,555
	Chevy Chase	2,850,500,770
	Circuit City	1,616,431,500
	Citibank	50,686,472,960
	Conseco	1,576,217,225
	Dillard	1,304,594,356
	Discover	38,237,796,718
	Fingerhut	1,755,943,016
	First Bank	1,565,497,719
	First Chicago	16,008,018,296
	First Consumers	1,109,717,820
	First National	2,093,617,519
	First NBC	870,018,682
	First Omni Bank	583,309,295
	First Union	2,030,172,328
	First USA	38,339,497,893
	Fleet	12,003,726,004
	FNANB	1,678,493,629
	Gloucester	3,141,702,728
	Golden	3,310,459,109
	Household Affinity	6,816,554,556
	J.C. Penney	1,450,364,003
	MBNA	59,638,028,249
	Mellon	1,097,160,560
	Mercantile	574,592,150
	Metris	9,667,022,951
	National City	2,036,754,852
	Nationsbank	3,142,226,053
	American Express – Paid Off	44,789,300,549
	Partners First	1,650,850,761
	Pass-Through Amortizing Credit Card Trusts	2,304,121,315
	Peoples	2,731,680,488
	Prime	2,081,294,200
	Providian	8,808,742,228
	Saks	1,253,624,751
	Sears	19,607,113,295
	Spiegel	2,125,718,166
	Target	4,240,068,455
	Universal Card	14,998,628,554
	Wachovia	2,664,505,212
	World Financial Network	2,205,152,370
	York Receivables	1,385,159,145
Commercial MBS	Aetna Commercial	198,881,838
	American Southwest Financial	225,524,583
	Amresco Commercial Mortgage	450,321,042
	Asset Securitization Corp	1,657,456,476
	Bamburgh Finance PLC	210,172,858
	Banc of America Commercial Mortgage	1,745,608,472

Bear Stearns Commercial Mortgage	1,211,979,100
Calwest Industrial	460,000,000
Capco	1,223,026,633
CDC Securitization Corp.	637,487,900
Chase Commercial Mortgage	2,641,393,807
Column Canada	335,000,000
Commercial Mortgage Corp.	6,158,430,375
Credit Suisse First Boston	3,501,078,371
Deutsche Mortgage	1,775,588,733
DLJ Commercial Mortgage	1,543,499,229
Dolerite Funding PLC	518,293,680
Duke Limited	923,121,968
Entertainment Properties	155,500,000
Eurohypo	1,079,108,461
European Loan Conduit (Coronis)	521,260,931
Falcon Trust	147,500,000
Fannie Mae	1,412,989,196
Fennica	800,088,262
First Boston Mortgage	16,444,246
First Union - Bank of America	3,241,929,068
Freddie Mac	489,239,059
GE Capital Commercial Mortgage	1,296,786,316
Ginnie Mae	3,073,422,698
Global Commercial One	1,473,356,824
GMAC Commercial Mortgage	3,460,474,918
Greenwich Capital	1,215,737,108
GS Mortgage	1,835,632,209
Heller Financial Commercial Mortgage	1,002,146,533
Homeside Mortgage	208,092,996
HOTELoC plc	531,189,000
ICCMAC	255,122,013
IMPAC Commercial	300,562,272
JP Morgan Chase	1,088,613,111
Keycorp	816,325,929
Lehman Brothers	6,180,317,960
Mansfield	265,236,739
Merrill Lynch	1,082,600,759
Midland Realty	459,687,004
Monument	363,252,659
Morgan Stanley	1,524,088,500
Mortgage Capital Funding	1,269,838,425
N-45 First CMBS Issuer Corp.	348,538,744
Nationslink Funding Corp.	1,553,352,054
New England Mutual Life Insurance	8,090,280
Nomura Asset Capital Corp.	3,658,309,253
Nymphenburg Ltd.	1,953,330,104
Paine Webber	700,149,435
Pan-European Industrial Properties SA	605,733,779
PNC Mortgage Acceptance Corp.	1,076,087,272
Prudential Commercial Mortgage	1,128,488,576

	S.C.I.P. Societa Cartolarizzazione Immobili Pubblici S.r.L.	7,797,103,600
	Salomon Brothers Mortgage	952,694,296
	Solar Trust	241,191,493
	Strategic Hotel Capital	700,000,000
	Structured Asset Securities Corp.	231,875,982
	UBS 400 Atlantic Street Mortgage Trust	29,779,310
	Wachovia Bank Commercial Mortgage	1,200,914,923
	Washington Mutual	579,949,968
	Werretown Supermarkets	575,000,000
	Westfield Shoppingtown Valley Fair Mall	49,736,241
	Wilshire Credit Corporation	41,379,000
	Windermere	467,000,000
Equipment Lease	ABFS Equipment	29,096,742
	Advanta Equipment	639,402,094
	Bank of America	533,886,750
	Capita Equipment	426,695,786
	Case Equipment	650,751,068
	Caterpillar Financial	682,740,575
	Charter Equipment	150,985,852
	CIT Equipment	1,111,563,967
	CNH Equipment	1,062,285,799
	Conseco Lease Finance	612,444,059
	Copelco Capital Funding Corp	910,005,277
	DVI Business Trust	583,893,906
	Fidelity Equipment	40,222,784
	First Sierra Equipment	211,000,000
	GE Capital Equipment	330,655,783
	General American Railcar Corp.	140,579,679
	GreatAmerica Leasing	255,299,894
	Heartland Bank Lease	3,638,472
	Heller Equipment	363,730,337
	IKON Receivables Funding LLC	872,143,360
	John Deere	931,575,802
	Locat	635,359,423
	New Holland Equipment	1,003,830,671
	Newcourt Equipment	1,666,866,238
	ORIX Credit Alliance	317,044,171
	PBG Equipment	257,428,393
	Textron Financial Corporation	390,439,753
	XEROX Equipment Lease	536,874,239
Dealer Floorplans	Bombardier	904,427,666
	CARCO Auto Loan	10,372,346,293
	Conseco Floorplan	2,263,032,180
	CRAFT	475,980,259
	DaimlerChrysler	10,355,469,428
	Distribution Financial Services	3,698,422,346
	Ford Credit Auto Loan	11,413,354,679
	GMAC SWIFT	6,267,192,851

	GreenTree Conseco	2,263,032,180
	Navistar Financial	952,794,732
	Superior Wholesale Inventory Financing	5,610,926,399
	Volkswagen Credit	694,836,000
	Yamaha Motor	697,625,668
Home Equity Loans	125 Home Loan	223,488,448
	Aames Mortgage	314,957,989
	ABFS Mortgage	379,745,061
	Access Financial	53,740,986
	Accredited Mortgage Loan	140,387,619
	Ace	723,658,930
	Advanta Home Equity	1,119,546,539
	AFC Mortgage	1,996,640,922
	American Mortgage	344,782,310
	Ameriquest Mortgage	1,699,997,433
	AmerUs Home Equity	32,440,484
	Amortizing Residential	2,921,818,509
	AMRESCO	510,730,235
	Asset Backed Funding Corporation	1,171,311,288
	Associates Home Equity	118,737,119
	Avondale Home Equity	21,155,028
	Banc One Home Equity	270,556,176
	Bank of America Mortgage	600,022,612
	BankBoston Home Equity	363,358,679
	Bayview Financial	258,664,870
	Bear Stearns	1,346,558,186
	Beneficial Mortgage Corporation	325,540,956
	Block Mortgage Finance Inc.	302,704,355
	Bosque	13,251,171
	C-BASS Mortgage	394,425,807
	CDC Mortgage	549,805,620
	Cendant Mortgage	256,424,694
	Centex Home Equity	600,000,452
	Champion Home Equity	337,151,287
	Chase Mortgage Finance	1,271,948,949
	Chevy Chase Home Loan	48,920,866
	CIT Home Equity	940,000,000
	CitiFinancial Mortgage	890,732,000
	City Capital Home Loan	227,349,726
	Cityscape Home Equity	124,422,634
	CMC III	216,501,417
	Compass	754,429,042
	Conseco Finance Corp.	1,210,074,173
	ContiMortgage Corporation	1,171,805,574
	CoreStates Financial Corporation	52,302,686
	Countrywide	1,717,300,000
	Credit Suisse First Boston	3,017,424,995
	Credit-Based Mortgage Loan	254,309,823
	CTS Home Equity	8,755,538

Delta Funding Corporation	649,061,815
DiTech Home Loan	210,954,004
DLJ Mortgage	1,066,060,575
Empire Funding	262,213,278
EQCC Home Equity	11,177,317,154
Equicon Mortgage	16,360,752
Equity One Mortgage	511,242,780
EquiVantage Home Equity	41,000,518
Fairbanks Capital	126,307,708
Fidelity Funding	22,488,913
First Alliance Mortgage	77,613,264
First City	79,124,600
First Franklin	1,098,000,000
First Greensboro Home Equity	72,439,000
First Republic Mortgage	408,630,379
First Union Home Equity	238,933,166
FirstPlus Home Loan	587,809,393
FNM Mortgage	2,554,841
Fremont Home Loan	486,659,002
Fund America	129,473,879
FURST	76,671,524
GE Capital Mortgage Services Inc	528,930,322
GMAC Mortgage	1,602,767,707
Golden National Mortgage	119,377,562
GreenPoint	348,915,646
Greenwich	30,990,955
GSAMP	220,269,319
Guardian Savings and Loan	18,991,155
Hanover Capital	93,460,950
Headlands Mortgage	199,707,518
HomeGold Home Equity	79,413,800
HomEq Residential	1,976,390,624
Household Home Equity	1,312,913,741
ICIFC	117,693,459
IMC Home Equity	656,581,667
Impac	1,886,899,267
IndyMac	1,021,622,389
Irwin	877,320,628
Keystone	472,249,899
Lehman Home Equity	128,872,823
Life Financial	274,841,472
Long Beach	2,000,000,169
Master Financial	240,520,269
MDC Mortgage Funding	6,336,188
Mego Mortgage	63,710,882
Mellon Bank	1,058,055,984
Merrill Lynch	810,397,216
MESA	38,745,000
Metropolitan Asset Funding	301,175,000
Merrill Lynch Home Equity	149,780,873

	Morgan Stanley	983,630,497
	Mortgage Lenders Network	214,136,037
	Nationscredit	75,562,854
	New Century Home Equity	1,173,606,089
	New South Home Equity	352,380,454
	NISTAR	440,353,011
	Nomura	26,676,253
	Norwest	79,236,237
	Novastar Home Equity	1,461,014,974
	Novus	272,684,821
	Ocwen Mortgage	616,316,414
	Option One Mortgage	1,599,998,923
	Pacific Southwest Bank	134,917,860
	PacificAmerica Home Equity	89,850,177
	Preferred Mortgage	15,602,549
	Provident Bank	615,000,000
	Prudential	27,436,140
	RAFC	880,293,000
	RBMG Funding Co.	92,321,316
	Renaissance Mortgage	230,042,752
	Republic Bank	196,624,453
	Residential Accredit	2,100,001,482
	Ryland Mtg	25,699,955
	SACO	312,418,733
	Salomon Brothers Finance	999,424,780
	Saxon	699,817,756
	Security National Mortgage	84,293,490
	Soundview Home Equity	228,191,384
	Southern Pacific	358,977,384
	Structured Asset Investment	1,284,918,793
	The Money Store	390,331,106
	UCFC Home Equity	647,816,921
	United National	186,069,085
	United PanAm Mortgage	105,838,807
	Wachovia	950,000,000
	Washington Mutual Mortgage	1,299,312,842
	Wells Fargo	229,384,771
	Wilshire Funding Corp	129,533,663
	WMC	2,291,155,492
Marine/Boat Loans	BankBoston	187,624,960
	CBNJ	9,038,918
	Chase Manhattan	116,961,952
	CIT Marine	589,689,727
	Distribution Financial Services Marine	487,112,179
	NationsCredit	86,318,722
	Sterling Bank	12,485,313
MBS	ABN AMRO	620,329,602
	American General Mortgage	259,009,662

American Mortgage	8,843,931
Amortizing Residential	579,244,273
ARENA B.V.	1,099,999,993
ARES Finance S.A.	1,540,493,490
Ayt 11 Fondo de Titulizacion Hipotecaria	403,000,000
Bank of America Mortgage	1,588,122,437
Bank One	1,052,170,596
Bear Stearns	2,330,289,891
BPM	1,340,000,000
BPV Mortgages	512,495,057
California Federal Bank	55,014,851
Celtic Residential	642,613,919
Cendant Mortgage	137,206,326
Chase Mortgage	688,132,083
Citicorp Mortgage	570,239,433
Claris Finance	383,000,000
CMC	387,425,972
Countrywide	700,000,000
Credit Suisse First Boston	1,740,538,873
Crusade Global	1,786,956,520
CW Independent National Mortgage	663,727,947
Delphinus	1,702,250,000
DOMOS	1,125,051,169
Dutch MBS B.V.	766,760,854
Eerste Vlaamse Effectisering N.V.	267,259,589
Electra	738,123,486
Emerald Mortgages PLC	452,737,117
Fifth Third Mortgage	488,790,595
Finance For People PLC	167,803,000
Financial Asset Securitization Inc	70,092,431
First Flexible PLC	470,640,169
First Horizon Mortgage	23,156,259
First Union National Bank	292,103,161
Fleet Home Equity	806,069,334
Fondo de Titulizacion Hipotecaria Banesto	1,037,938,994
GE Capital	533,654,033
Giotto Finance SPA	1,062,011,833
Glendale Federal Bank	18,917,616
GMAC Mortgage	871,024,848
Granite Finance	3,463,940,128
Grecale S.r.l.	182,886,695
Greenwich Capital	27,449,029
GSRPM Mortgage	257,141,789
Hanover SPC-2 Inc.	195,588,038
Harborview Mortgage	370,717,334
Headlands Mortgage	211,780,135
Holland Euro-Denominated Mortgage-Backed	1,250,117,500
Holmes Financing PLC	25,093,964,278
Home Owners Federal Savings	10,689,701
Homeloans PLC	199,606,000

	Household Mortgage	1,130,116,218
	Huntington Residential Mortgage	14,992,804
	Ilse PLC	58,150,284
	Impac	254,227,459
	IndyMac	336,686,830
	Loggias	588,792,437
	MasterDomos	1,797,505,795
	MASTR	1,550,226,398
	Mecenate S.R.L.	357,214,350
	Mellon Bank Mortgage	815,143,228
	Merrill Lynch Mortgage	88,010,045
	Metropolitan Asset Funding	53,040,207
	Mid-State	496,068,437
	Morgan Stanley	708,903,128
	Mortgages PLC	319,668,010
	Mound Financing PLC	1,566,560,169
	MRFC Mortgage	504,055,876
	Nationsbanc Montgomery Funding	278,720,022
	New England Mutual Life	19,164,434
	Norwest	892,126,631
	Novastar Mortgage	788,000,100
	Orio Finance PLC	430,728,711
	PaineWebber Mtg	35,857,228
	Paragon Mortgages	486,734,000
	Permanent Financing PLC	9,107,048,165
	PNC Mortgage	506,158,477
	Preferred Residential	200,000,000
	Provide Gems	1,052,083,974
	Prudential Home Mortgage	557,609,634
	PUMA Masterfund	746,249,994
	Residential Accredit Loans Inc.	1,442,207,075
	Resolution Trust Corporation	394,540,908
	RMAC PLC	1,111,912,891
	Saecure B.V.	784,650,548
	Salomon Brothers	662,280,944
	Saxon Mortgage Pool 1	38,311,055
	Sears Mtg	17,821,971
	Seashell	479,615,284
	Sequoia Mortgage	1,120,993,195
	Sharps SP I LLC	714,625,163
	Structured Asset Mortgage	1,217,864,858
	SwAFE I B.V.	707,089,153
	Upgrade S.p.A.	507,557,388
	Velites S.r.l.	297,202,036
	Washington Mutual Bank	5,989,486,307
	Wells Fargo	1,200,437,433
Manufactured Housing	Access Financial	102,709,842
	Ace	176,931,307
	Associates	2,467,088,944

	BankAmerica	687,788,876
	Bombardier Capital	463,430,672
	CIT Group	118,677,807
	Conseco Finance Corp.	1,968,345,509
	CSFB	107,528,616
	Daiwa Mortgage	41,078,926
	Deutsche Financial	183,657,287
	FirstFed Corp.	35,889,673
	GreenPoint	774,760,176
	Greenwich Capital	64,693,206
	IndyMac	184,835,388
	Lehman	1,387,634,652
	Madison Avenue	418,860,397
	Merit	410,561,022
	Merrill Lynch Mortgage	70,566,352
	Oakwood Mortgage	351,845,108
	Origen	163,350,000
	Resolution Trust Corp	37,692,505
	Security Pacific	59,397,838
	Signal	43,838,749
	UCFC Funding Corporation	141,418,387
	Vanderbilt Acquisition	800,000,000
	Western Savings	18,258,851
	Wilshire Manufactured Housing	7,943,147
Other Consumer Loans	Aegis S.r.l.	525,000,000
	AyT 7 Promociones Inmobiliarias I	319,864,529
	CIC Conso	290,859,834
	Conseco Recreational, Equipment & Consumer	541,838,250
	Du.Ca. SPV SRL	502,998,107
	FE Blue S.r.l.	1,593,966,535
	Fondo de Titulizacion de Activos Consumo Santander 1	1,080,002,887
	Household Consumer Loan	1,934,439,685
	Italease Finance SPA	579,771,544
	Lombarda Lease Finance S.r.l.	610,007,863
	Mercantile Finance SRL	300,117,365
	Noria 3	149,749,703
	Nova Finance No. 1 Ltd	352,133,718
	Paragon Auto and Secured Finance PLC	453,691,000
	SF Funding	19,309,386,365
	Sky Financial	125,853,024
	Sterling Consumer Loan	23,215,899
	Trevi Finance SPA	2,751,166,854
	Upgrade S.p.A.	226,096,645
Recreational Vehicle	ACE RV and Marine	308,072,046
	BankBoston Recreational Vehicle	388,446,853
	Chase Manhattan RV	409,616,372
	CIT RV	576,068,337
	Conseco Finance Recreational Enthusiast	609,410,972

	Distribution Financial Services RV	822,708,956
	Fleetwood Credit	161,891,157
	NationsCredit RV	20,114,647
	SSB RV	647,942,733
Student	Access Group, Inc.	265,066,793
	Keycorp Student Loan	911,647,123
	Nelnet Student Loan	1,016,738,461
	SLM Private Credit	3,535,369,562
	SMS Student Loan	1,153,664,375
	University Support Services Inc.	69,550,678
	Wells Fargo Student Loan	554,147,000

Appendix B: Mapping Performance to Value in Asset-backed Securities

The value of an asset-backed security lies in the seniority of payments to different classes of notes and bonds sold to investors and the size and composition of the underlying credit enhancement.

Periodic payments are made to investors in a waterfall. Senior investors are paid first, followed by the next junior class, and so on until all available cash is distributed that period. If additional cash remains after investors are paid, that cash is used to fund the credit enhancements. Cash remaining after distribution to those accounts is called excess spread.[1]

Credit enhancements and excess spread are crucial to insuring that enough cash exists to pay investors in each period's waterfall. If there exists a cash shortfall from collateral payments, cash may be drawn first from the excess spread, and then from the credit enhancements, to cover the shortfall that period. Hence excess spread is the first buffer against investor loss.

Inadequate excess spread is a sign that the pool is not producing the cash payments predicted by the originator. That does not mean that the underlying collateral is inadequate or poorly underwritten (although these causes should not necessarily be ruled out). It may just mean that originator's statistical payment model did not predict well for the present pool.

If the shortfall is merely a matter of inaccurate statistical prediction, the situation may not be serious. Two possibilities typically emerge. First, investors may agree to renegotiate the terms of the waterfall and associated interest and fee payments in order to preserve their investments. This is a common way of resuscitating weak pools in the credit card sector and discussed at length in Higgins and Mason (2003). The most recent incident was the Good Friday announcement by Chase in 2003. Second, the pool may enter early, or accelerated, amortization. In an early amortization scenario, investors are repaid their principal on an accelerated basis prior to the contracted maturity. In either case, there is technically no default and typically no ratings downgrade.

Excess spread shortfalls that are associated with something other than model errors, however, typically indicate severe problems with the originator and their business

[1] The originator of the collateral has a residual interest in the trust, and hence takes possession of any remaining cash balances upon the maturity of the deal (assuming all investors have been paid in full).

strategy. Such problems are doubly important in asset-backed securities because the originator is typically hired as the servicer of the collateral on behalf of investors. Hence problems with the originator will spill through to investors in the form of less effort toward mailing monthly billing statements, lower monthly collections, and reduced recoveries from late and slow customers and, ultimately, less cash contributed to the waterfall each period.

In either circumstance, it is not surprising that excess spread is typically identified as a contractual trigger for early amortization. Almost all asset-backed security documents specify that if the three-month moving average excess spread falls below zero, all security classes will enter early amortization.

Excess spread is also a key component of the value of asset-backed securities. All else held constant, greater distance from zero excess spread creates greater certainty that all investor payments will be made in full and on schedule. In other words, default risk is lower for the same contracted terms, which adds value to the investment.[2]

Excess spread itself, however, is not always easy to monitor. While some older pool structures include a single excess spread account, newer structures often include multiple accounts, some of which are specific to a single note class.

Nonetheless, there are only really three sources of pressure to excess spread: chargeoffs, payment rates, and loan portfolio yields. An example shows how these three factors influence excess spread.[3]

1. Baseline ABS Performance Scenario

Start with a baseline scenario. Suppose we have the credit card pool in Table 1 in which there are $112 million in receivables in the pool. The investors have claim to $100 million and the seller has claim to $12 million because the pool is overcollateralized (as per Gorton and Pennacchi 1995). Hence the investors' share of the pool is 89%.

Assume a 5% chargeoff rate, which remains constant over time. Hence in month one there are $467,000in charged-off loans in the pool, $417,000of which are pro rated to investors.

[2] Recognizing this relationship, Basel II proposes that banks begin accumulating capital to cover the early amortization when Excess Spreads fall below 450 basis points.

[3] The following example is adapted from a presentation by Mark Adelson, Director and Head of Structured Finance Research, Nomura Securities International, at the Federal Reserve Bank of Philadelphia Payment Cards Center on October 25, 2002.

The pool yield is 18%, hence finance charges of $1,680,000 accrue during the first month, $1,500,000 of which are pro rated to investors. Out of this $1,680,000, the trust must pay the 10% coupon ($833,000) due on bonds sold to the investors, 2% servicing fees ($167,000), and cover investors' share of chargeoffs of $417,000. There is $83,000 left after coving expenses.

The principal payment rate on the pool is 15% per month, so $16,800,000 was collected on principal in the first month. On the prorated basis, $15,000,000 of these chargeoffs is owned by investors.

Since this is a revolving credit card pool, the $15,000,000 collected on principal plus the $417,000 from investors' chargeoffs (taken from the yield) are reinvested in new receivables that are added into the pool for subsequent months until amortization. Since the pool is not currently in amortization, zero principal is repaid to investors this month and the amount of bonds outstanding remains at $100,000,000.

Assuming a 48-month revolving phase, the baseline scenario in Table 1 enters the amortization phase in the 49th month. At this point, principal collections are paid out to bondholders instead of being used to purchase new receivables. Supposing the pool is structured so that 85% of principal collections (the pro rata investors share of the pool in the first month of amortization) plus 100% of the investors' share of chargeoffs are repaid to investors each month during amortization, the principal in the pool in Table 1 is repaid about seven months after the period in which amortization begins.

2. Chargeoff Stress ABS Performance Scenario

Now assume that the pool does not perform so well. Suppose that the chargeoff rate rises, perhaps because of an unexpected macroeconomic shock. Chargeoffs are now 6% in month 24, 7% in month 25, 9% in month 26, and eventually reach 20% in month 31.

The one percent increase in chargeoffs is enough to reduce excess spread to zero in month 24, and excess spread becomes negative thereafter. Suppose that one month (rather than the typical three) negative excess spread triggers early amortization on the pool. The pool enters early amortization in month three, and investors begin to receive principal payments at that time.

Because chargeoffs now exceed the portfolio yield, the pool enters early amortization and proceeds from principal payments are used to repay investors. Supposing the pool is structured so that 85% of principal collections (the pro rata investors share of the pool in the first month of amortization) plus 100% of the investors' share of chargeoffs are repaid to investors each month during amortization, the principal in the pool in Table 2 is repaid about eight months after the period in which amortization began, only slightly slower than the baseline scenario. Note, however, that investors may receive that principal *substantially sooner* than the date of maturity stipulated in the bonds because of the early amortization feature. Hence while there has technically been no default (investors receive principal and interest in full), investors face reinvestment risk.

3. Chargeoff and Payment Rate Stress ABS Performance Scenario

If economic conditions are such that more loans are defaulting, customers who do not default are probably less likely to make more than their minimum monthly payment or lower the excess they do pay. Hence the pool experiences not only a higher chargeoff rate, but also a lower payment rate. We can extend the previous example to add declining payment rates to the increased chargeoff scenario.

Table 3 illustrates the combined scenario. In the present scenario, payment rates decline to 14% in month 23, trending down eventually to 7% in month 28. Again, the stress scenario results in early amortization beginning in month 24. However, the lower payment rate now reduces the amount of principal collections that are distributed to investors each month in early amortization. Hence investors are not fully repaid until month 34 in this scenario (rather than month 30 previously).

4. Chargeoff, Payment Rate, and Yield Stress ABS Performance Scenario

A typical monetary policy response to poor economic conditions is to try to reduce interest rates to stimulate borrowing. Hence, floating rate consumer loan interest rates will adjust downward and mortgage borrowers will refinance.[4] Both these influences result in lower pool yields.

Table 4 presents a scenario with higher chargeoffs, lower payment rates, and lower yields. Now we allow yields to decline beginning in month 23, trending down to a 10% steady state in month 27.

This time, the pool enters early amortization earlier than in the past (month 23 instead of month 24). As a result, amortization begins before chargeoffs and payment

[4] As mortgage loans are refinanced the highest rate loans will are paid off first, increasing pool Payment Rate but reducing yield.

rates are as bad as when amortization began previously. Hence, although it takes ten months to amortize the pool, investors are fully repaid in month 32 (instead of month 34 as in the chargeoff and payment rate scenario).

Table B1: ABS Waterfall – Baseline Scenario

Month	47	48	49	50	51	52	53	54	55	56	57	58	59
RECEIVABLES	112,000	114,000	118,000	113,000	111,000	115,000	119,000	122,000	125,000	126,000	124,000	125,000	127,000
Investors	**100,000**	**100,000**	**100,000**	**84,583**	**69,471**	**54,740**	**39,621**	**24,118**	**8,362**	**-**	**-**	**-**	**-**
Seller	12,000	14,000	18,000	28,417	41,529	60,260	79,379	97,882	116,638	126,000	124,000	125,000	127,000
Investors share	**89%**	**88%**	**85%**	**75%**	**63%**	**48%**	**33%**	**20%**	**7%**	**0%**	**0%**	**0%**	**0%**
Charge-off Rate	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%	5%
Charge-offs	467	475	492	471	463	479	496	508	521	525	517	521	529
Investors share	**417**	**417**	**417**	**352**	**289**	**228**	**165**	**100**	**35**	**-**	**-**	**-**	**-**
Yield	18%	18%	18%	18%	18%	18%	18%	18%	18%	18%	18%	18%	18%
Finance Charges	1,680	1,710	1,770	1,695	1,665	1,725	1,785	1,830	1,875	1,890	1,860	1,875	1,905
Investors share	**1,500**	**1,500**	**1,500**	**1,269**	**1,042**	**821**	**594**	**362**	**125**	**-**	**-**	**-**	**-**
Coupon (10%)	833	833	833	705	579	456	330	201	70	-	-	-	-
Fees (2%)	167	167	167	141	116	91	66	40	14	-	-	-	-
Charge-offs	417	417	417	352	289	228	165	100	35	-	-	-	-
Excess	83	83	83	70	58	46	33	20	7	-	-	-	-
Princ. Paymt Rate	15%	15%	15%	15%	15%	15%	15%	15%	15%	15%	15%	15%	15%
Princ. Collected	16,800	17,100	17,700	16,950	16,650	17,250	17,850	18,300	18,750	18,900	18,600	18,750	19,050
Investors share	**15,000**	**15,000**	**15,000**	**14,760**	**14,442**	**14,891**	**15,338**	**15,655**	**15,972**	**-**	**-**	**-**	**-**
Princ. Reinvested	15,417	15,417	-	-	-	-	-	-	-	-	-	-	-
Princ. Paid	-	-	15,417	15,112	14,731	15,119	15,503	15,756	8,362	-	-	-	-
BONDS	**100,000**	**100,000**	**84,583**	**69,471**	**54,740**	**39,621**	**24,118**	**8,362**	**-**	**-**	**-**	**-**	**-**

Table B2: ABS Waterfall – Chargeoff Stress Scenario

Month	22	23	24	25	26	27	28	29	30	31	32	33	34
RECEIVABLES	112,000	114,000	118,000	113,000	111,000	115,000	119,000	122,000	125,000	126,000	124,000	125,000	127,000
Investors	**100,000**	**100,000**	**100,000**	**84,417**	**68,743**	**53,330**	**37,512**	**21,402**	**5,240**	**-**	**-**	**-**	**-**
Seller	12,000	14,000	18,000	28,583	42,257	61,670	81,488	100,598	119,760	126,000	124,000	125,000	127,000
Investors share	**89%**	**88%**	**85%**	**75%**	**62%**	**46%**	**32%**	**18%**	**4%**	**0%**	**0%**	**0%**	**0%**
Charge-off Rate	5%	6%	7%	9%	11%	13%	15%	17%	19%	20%	20%	20%	20%
Charge-offs	467	570	688	848	1,018	1,246	1,488	1,728	1,979	2,100	2,067	2,083	2,117
Investors share	**417**	**500**	**583**	**633**	**630**	**578**	**469**	**303**	**83**	**-**	**-**	**-**	**-**
Yield	18%	18%	18%	18%	18%	18%	18%	18%	18%	18%	18%	18%	18%
Finance Charges	1,680	1,710	1,770	1,695	1,665	1,725	1,785	1,830	1,875	1,890	1,860	1,875	1,905
Investors share	**1,500**	**1,500**	**1,500**	**1,266**	**1,031**	**800**	**563**	**321**	**79**	**-**	**-**	**-**	**-**
Coupon (10%)	833	833	833	703	573	444	313	178	44	-	-	-	-
Fees (2%)	167	167	167	141	115	89	63	36	9	-	-	-	-
Charge-offs	417	500	583	633	630	578	469	303	83	-	-	-	-
Excess	83	-	(83)	(211)	(286)	(311)	(281)	(196)	(57)	-	-	-	-
Princ. Paymt Rate	15%	15%	15%	15%	15%	15%	15%	15%	15%	15%	15%	15%	15%
Princ. collected	16,800	17,100	17,700	16,950	16,650	17,250	17,850	18,300	18,750	18,900	18,600	18,750	19,050
Investors share	**15,000**	**15,000**	**15,000**	**15,041**	**14,783**	**15,240**	**15,641**	**15,858**	**16,020**	**-**	**-**	**-**	**-**
Princ. Reinvested	15,417	15,500	-	-	-	-	-	-	-	-	-	-	-
Princ. paid	-	-	15,583	15,674	15,413	15,818	16,110	16,161	5,240	-	-	-	-
BONDS	**100,000**	**100,000**	**84,417**	**68,743**	**53,330**	**37,512**	**21,402**	**5,240**	**-**	**-**	**-**	**-**	**-**

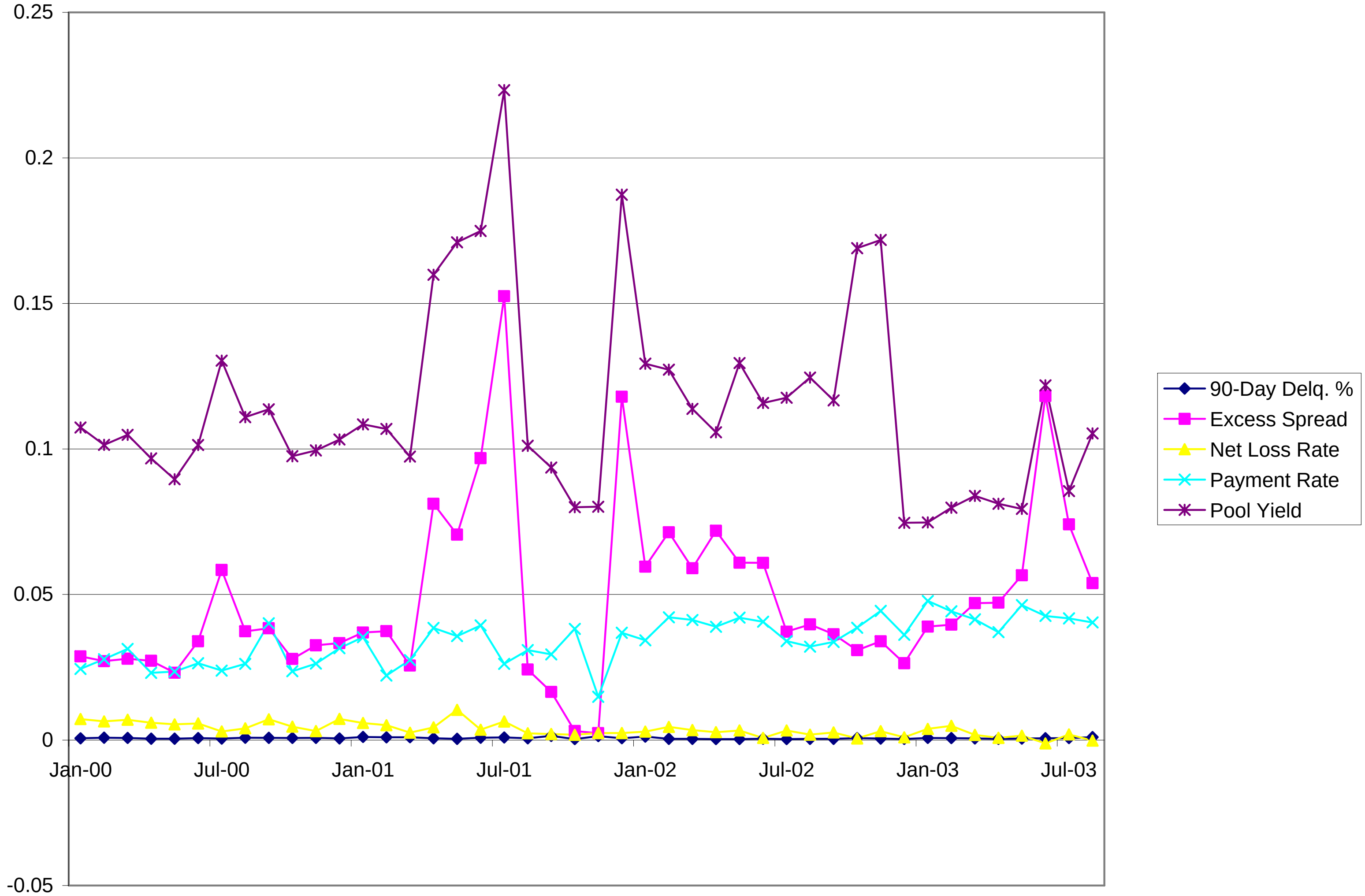
Table B3: ABS Waterfall – Chargeoff and Payment Rate Stress Scenario

Month	22	23	24	25	26	27	28	29	30	31	32	33	34
RECEIVABLES	112,000	114,000	118,000	113,000	111,000	115,000	119,000	122,000	125,000	126,000	124,000	125,000	127,000
Investors	**100,000**	**100,000**	**100,000**	**86,417**	**73,594**	**61,867**	**51,729**	**43,355**	**34,868**	**26,326**	**17,951**	**9,975**	**2,205**
Seller	12,000	14,000	18,000	26,583	37,406	53,133	67,271	78,645	90,132	99,674	106,049	115,025	124,795
Investors share	**89%**	**88%**	**85%**	**76%**	**66%**	**54%**	**43%**	**36%**	**28%**	**21%**	**14%**	**8%**	**2%**
Charge-off Rate	5%	6%	7%	9%	11%	13%	15%	17%	19%	20%	20%	20%	20%
Charge-offs	467	570	688	848	1,018	1,246	1,488	1,728	1,979	2,100	2,067	2,083	2,117
Investors share	**417**	**500**	**583**	**648**	**675**	**670**	**647**	**614**	**552**	**439**	**299**	**166**	**37**
Yield	18%	18%	18%	18%	18%	18%	18%	18%	18%	18%	18%	18%	18%
Finance Charges	1,680	1,710	1,770	1,695	1,665	1,725	1,785	1,830	1,875	1,890	1,860	1,875	1,905
Investors share	**1,500**	**1,500**	**1,500**	**1,296**	**1,104**	**928**	**776**	**650**	**523**	**395**	**269**	**150**	**33**
Coupon (10%)	833	833	833	720	613	516	431	361	291	219	150	83	18
Fees (2%)	167	167	167	144	123	103	86	72	58	44	30	17	4
Charge-offs	417	500	583	648	675	670	647	614	552	439	299	166	37
Excess	83	-	(83)	(216)	(307)	(361)	(388)	(397)	(378)	(307)	(209)	(116)	(26)
Princ. Paymt Rate	15%	14%	13%	12%	11%	9%	7%	7%	7%	7%	7%	7%	7%
Princ. collected	16,800	15,960	15,340	13,560	12,210	10,350	8,330	8,540	8,750	8,820	8,680	8,750	8,890
Investors share	**15,000**	**14,000**	**13,000**	**12,174**	**11,053**	**9,468**	**7,727**	**7,873**	**7,990**	**7,936**	**7,677**	**7,604**	**7,593**
Princ. Reinvested	15,417	14,500	-	-	-	-	-	-	-	-	-	-	-
Princ. paid	-	-	13,583	12,822	11,728	10,138	8,374	8,487	8,542	8,375	7,976	7,770	2,205
BONDS	**100,000**	**100,000**	**86,417**	**73,594**	**61,867**	**51,729**	**43,355**	**34,868**	**26,326**	**17,951**	**9,975**	**2,205**	**-**

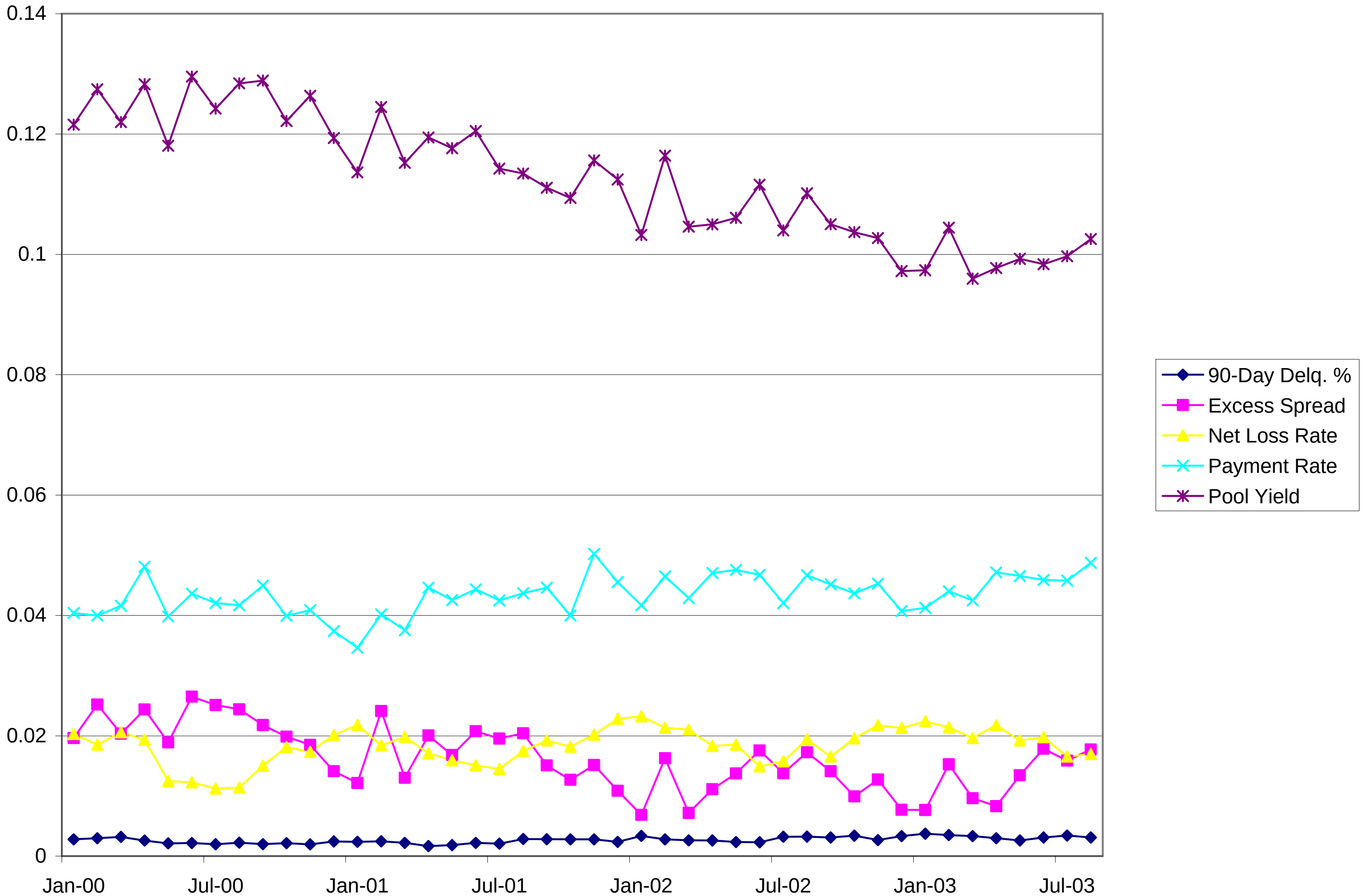
Table B4: ABS Waterfall – Chargeoff, Payment Rate, and Yield Stress Scenario

Month	22	23	24	25	26	27	28	29	30	31	32	33	34
RECEIVABLES	112,000	114,000	118,000	113,000	111,000	115,000	119,000	122,000	125,000	126,000	124,000	125,000	127,000
Investors	**100,000**	**100,000**	**85,500**	**73,886**	**61,252**	**49,751**	**39,875**	**31,798**	**23,638**	**15,452**	**7,440**	**-**	**-**
Seller	12,000	14,000	32,500	39,114	49,748	65,249	79,125	90,202	101,362	110,548	116,560	125,000	127,000
Investors share	**89%**	**88%**	**72%**	**65%**	**55%**	**43%**	**34%**	**26%**	**19%**	**12%**	**6%**	**0%**	**0%**
Charge-off Rate	5%	6%	7%	9%	11%	13%	15%	17%	19%	20%	20%	20%	20%
Charge-offs	467	570	688	848	1,018	1,246	1,488	1,728	1,979	2,100	2,067	2,083	2,117
Investors share	**417**	**500**	**499**	**554**	**561**	**539**	**498**	**450**	**374**	**258**	**124**	**-**	**-**
Yield	18%	16%	14%	12%	11%	10%	10%	10%	10%	10%	10%	10%	10%
Finance Charges	1,680	1,520	1,377	1,130	1,018	958	992	1,017	1,042	1,050	1,033	1,042	1,058
Investors share	**1,500**	**1,333**	**998**	**739**	**561**	**415**	**332**	**265**	**197**	**129**	**62**	**-**	**-**
Coupon (10%)	833	833	713	616	510	415	332	265	197	129	62	-	-
Fees (2%)	167	167	143	123	102	83	66	53	39	26	12	-	-
Charge-offs	417	500	499	554	561	539	498	450	374	258	124	-	-
Excess	83	(167)	(356)	(554)	(613)	(622)	(565)	(503)	(414)	(283)	(136)	-	-
Princ. Paymt Rate	15%	14%	13%	12%	11%	9%	7%	7%	7%	7%	7%	7%	7%
Princ. collected	16,800	15,960	15,340	13,560	12,210	10,350	8,330	8,540	8,750	8,820	8,680	8,750	8,890
Investors share	**15,000**	**14,000**	**11,115**	**12,080**	**10,940**	**9,336**	**7,579**	**7,709**	**7,812**	**7,755**	**7,502**	**-**	**-**
Princ. Reinvested	15,417	-	-	-	-	-	-	-	-	-	-	-	-
Princ. paid	-	14,500	11,614	12,634	11,501	9,875	8,077	8,160	8,186	8,012	7,440	-	-
BONDS	**100,000**	**85,500**	**73,886**	**61,252**	**49,751**	**39,875**	**31,798**	**23,638**	**15,452**	**7,440**	**-**	**-**	**-**

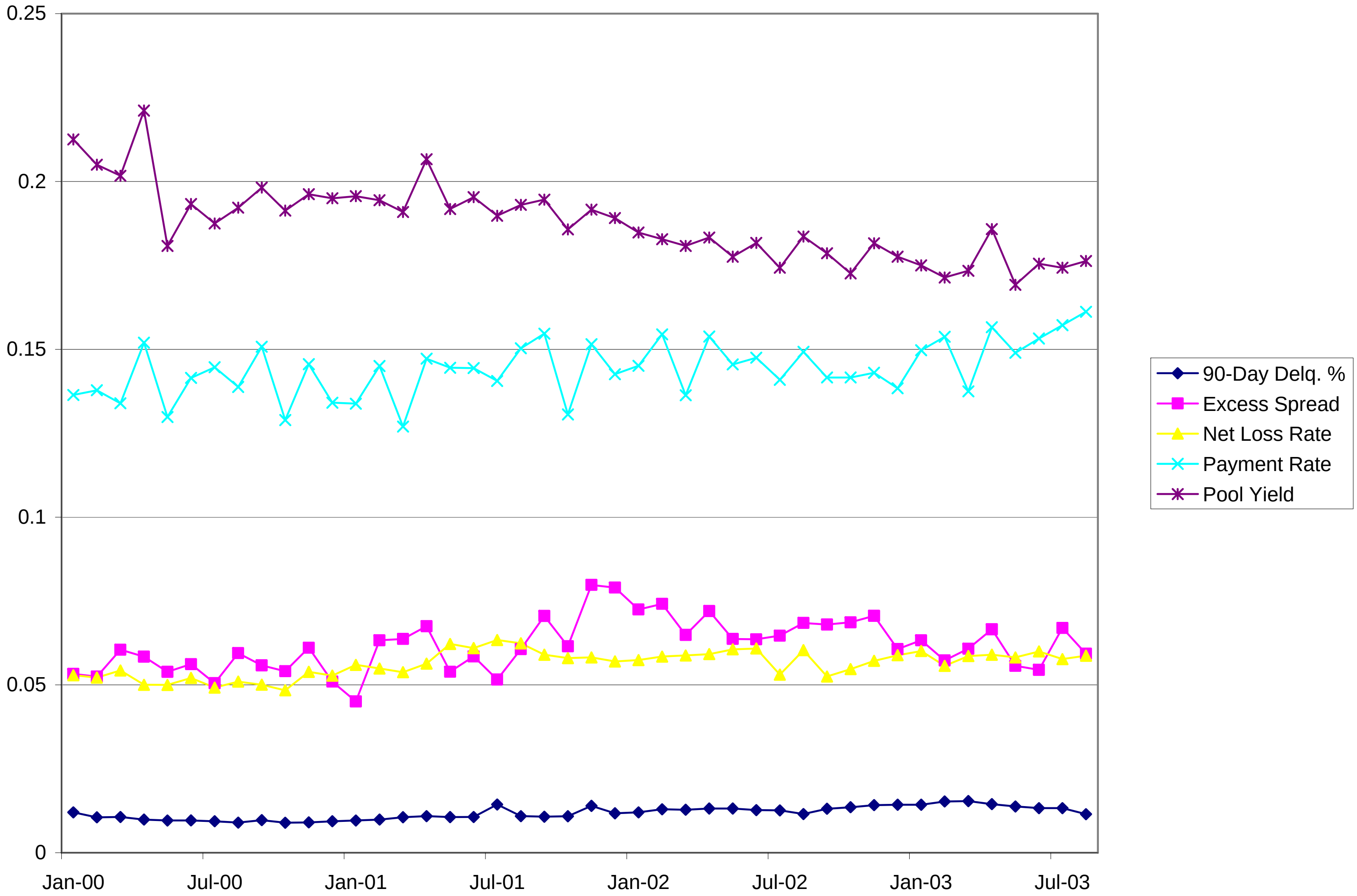
Appendix C, Figure C1
Median Performance Measures over Time for Auto Leases



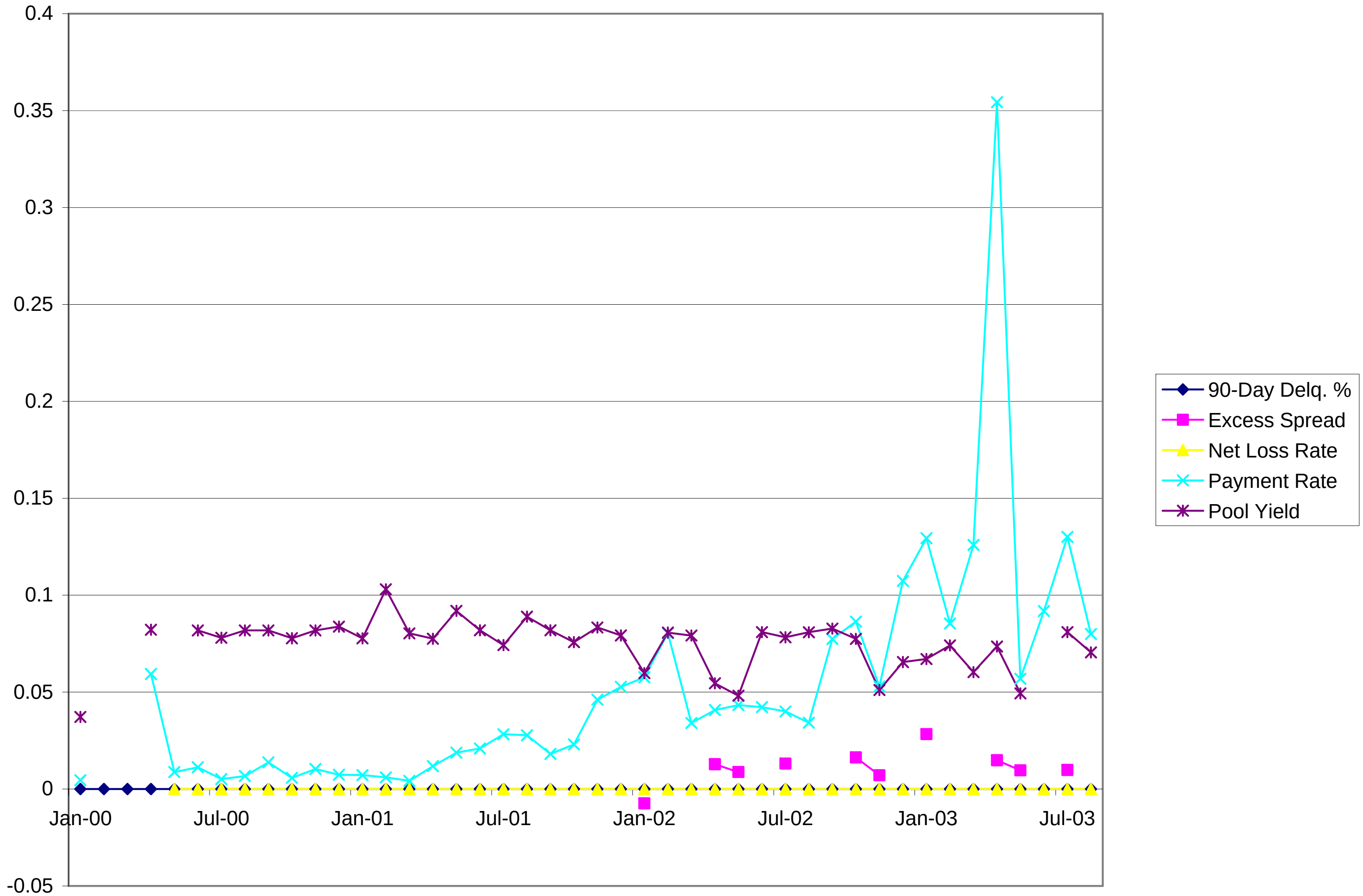
Appendix C, Figure C2
Median Performance Measures over Time for Auto Loans



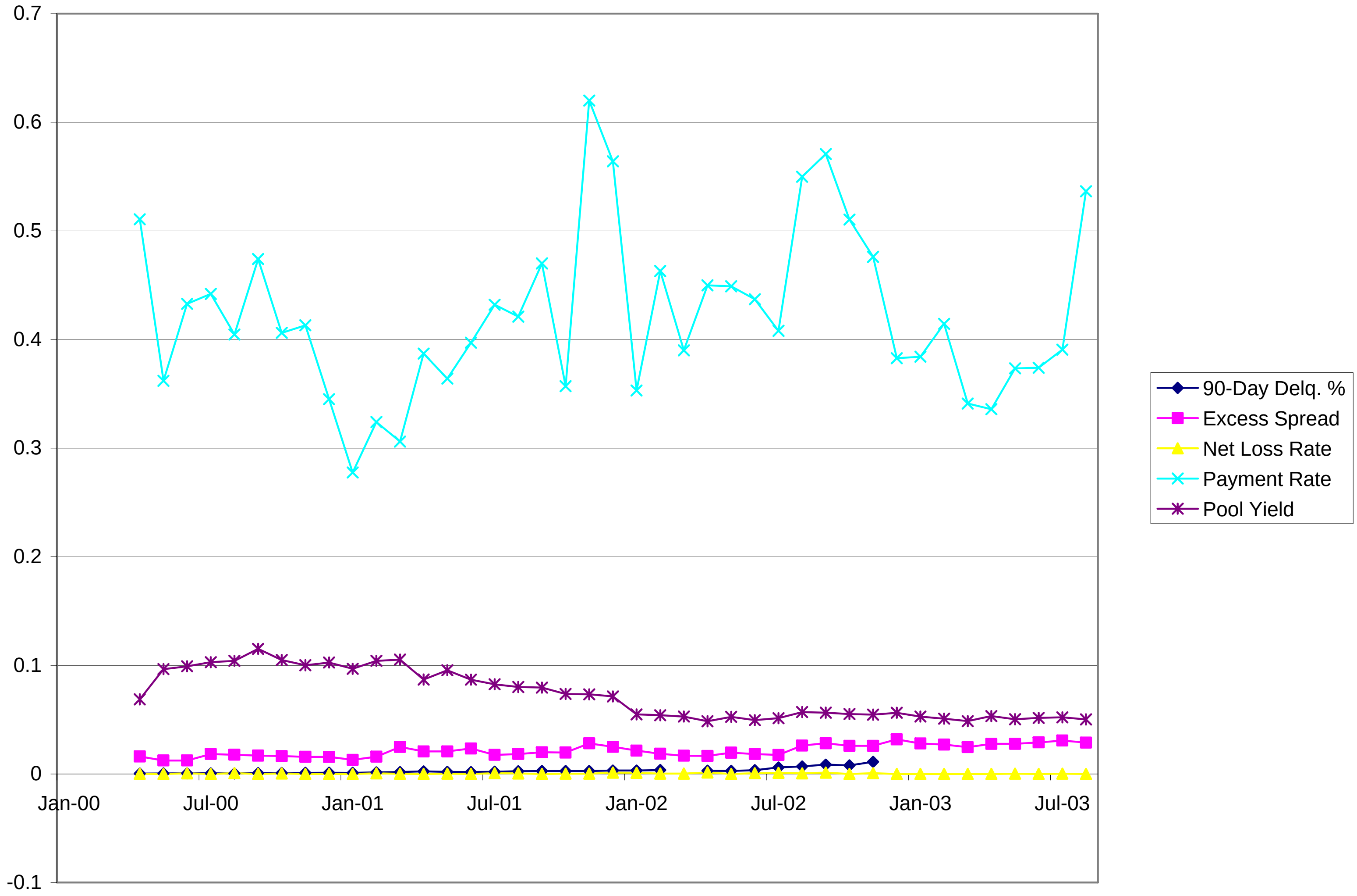
Appendix C, Figure C3
Median Performance Measures over Time for Credit Card Receivables



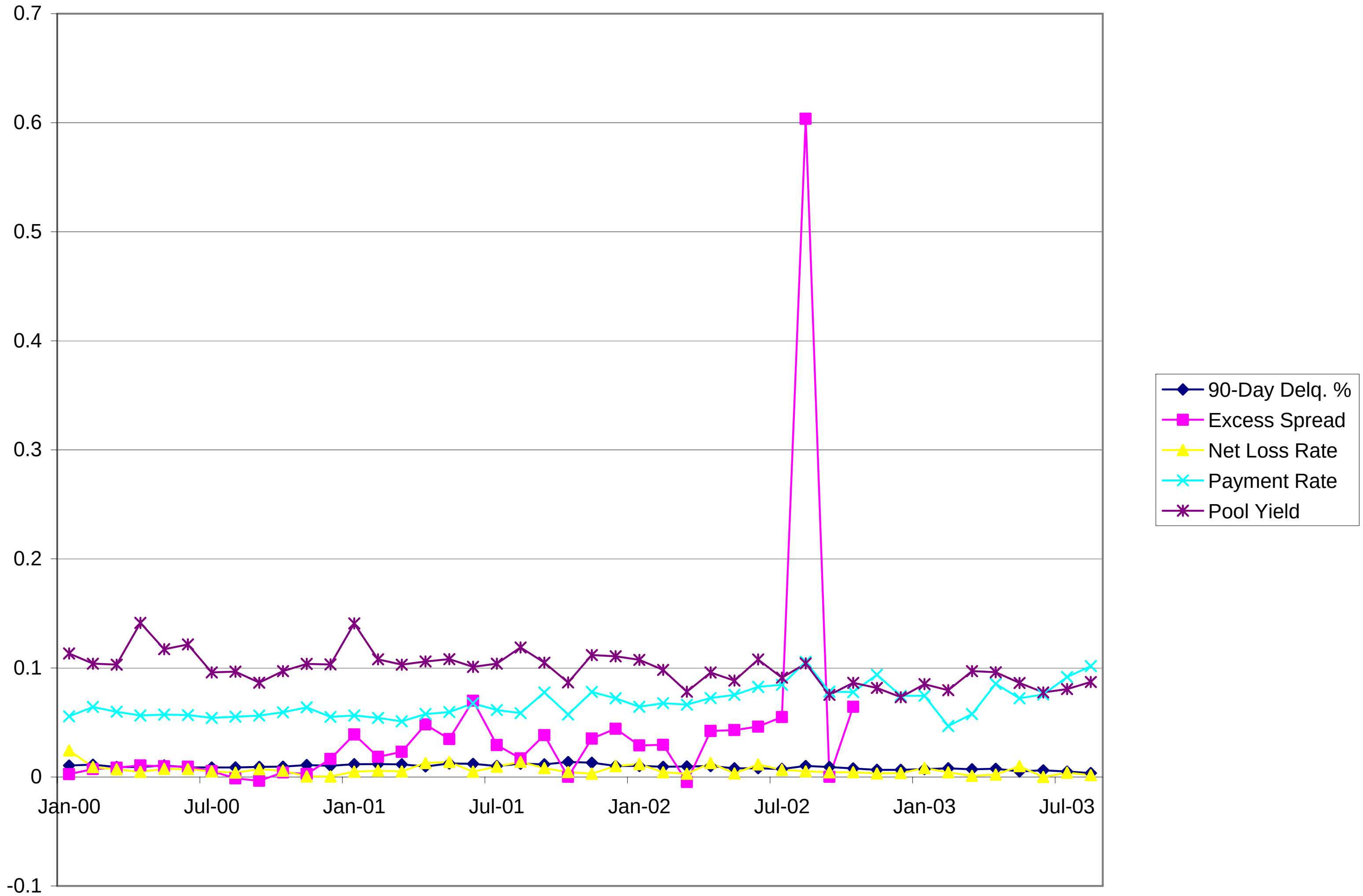
Appendix C, Figure C4
Median Performance Measures over Time for Commercial Mortgage Loans



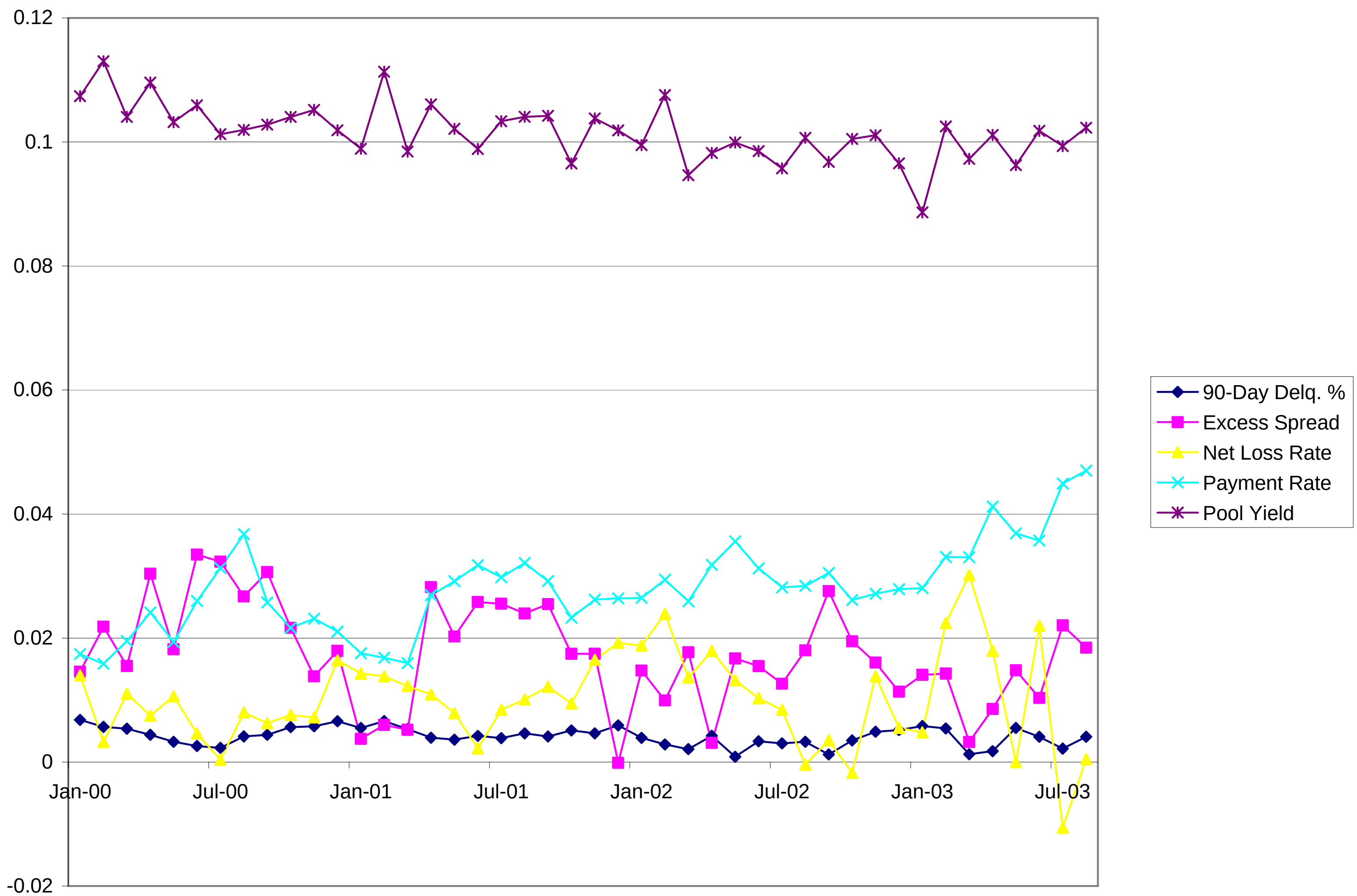
Appendix C, Figure C5
Median Performance Measures over Time for Dealer Floorplan Loans



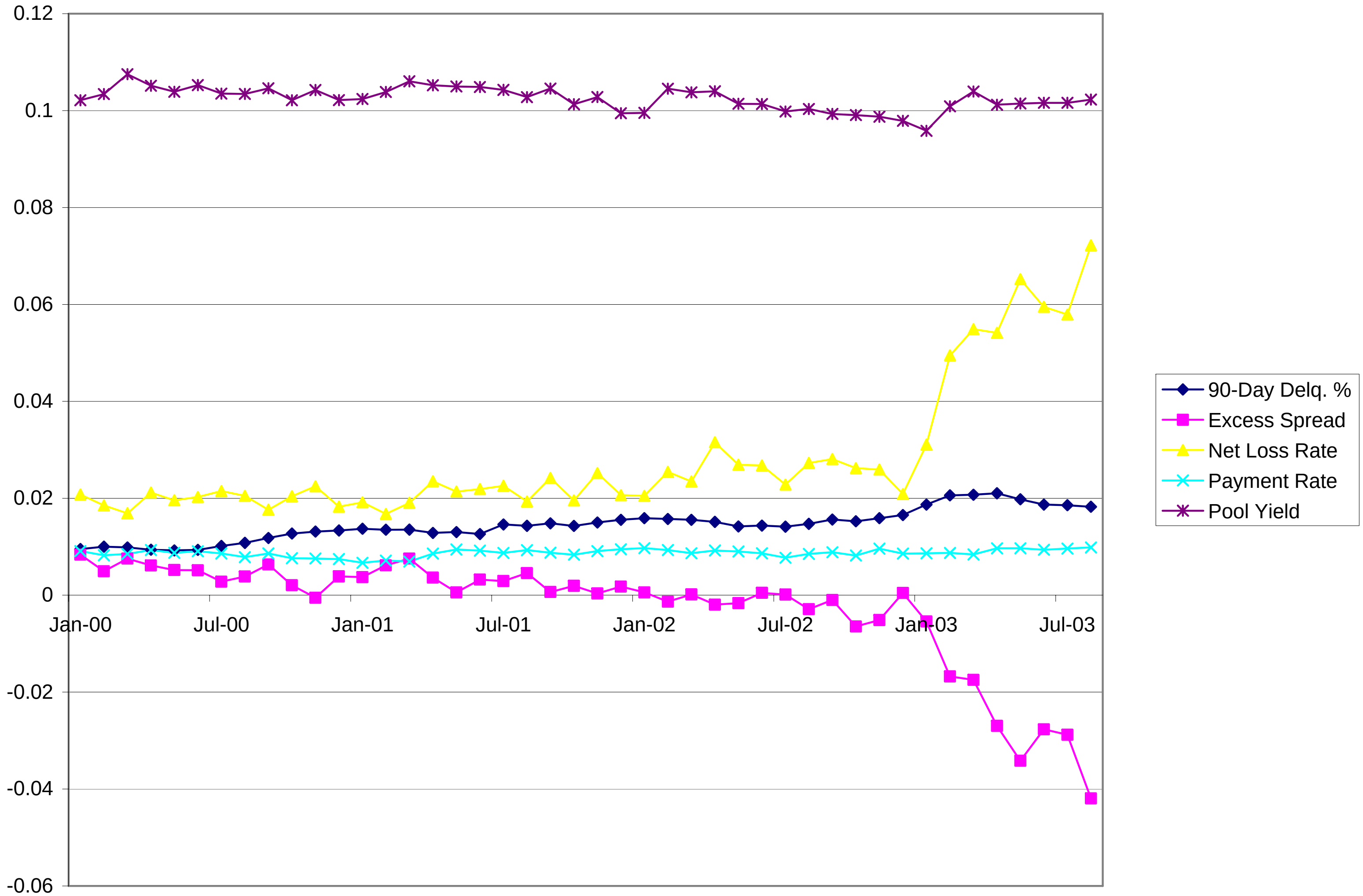
Appendix C, Figure C6
Median Performance Measures over Time for Equipment Leases



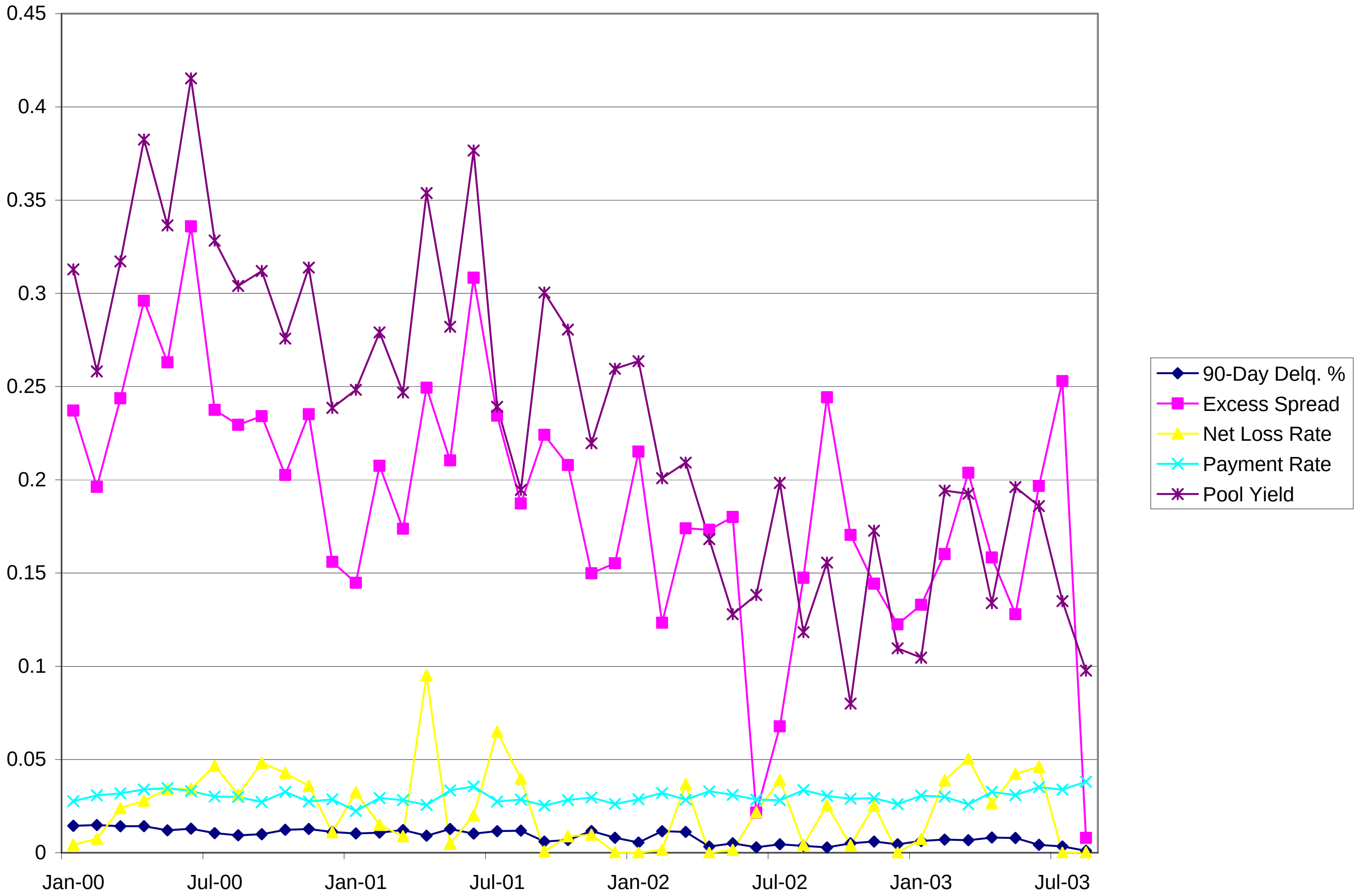
Appendix C, Figure C7
Median Performance Measures over Time for Marine and Boat Loans



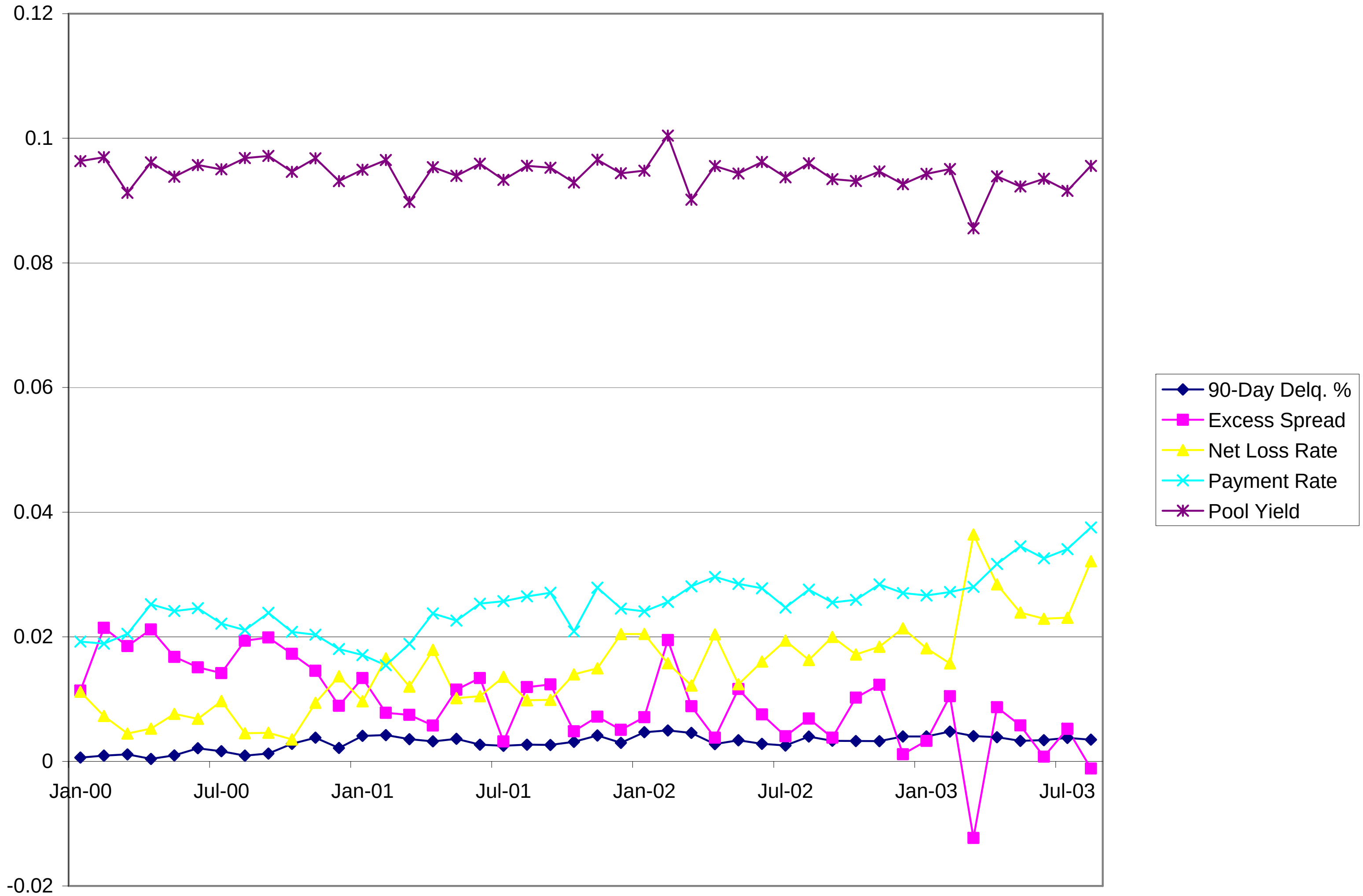
Appendix C, Figure C8
Median Performance Measures over Time for Manufactured Home Loans



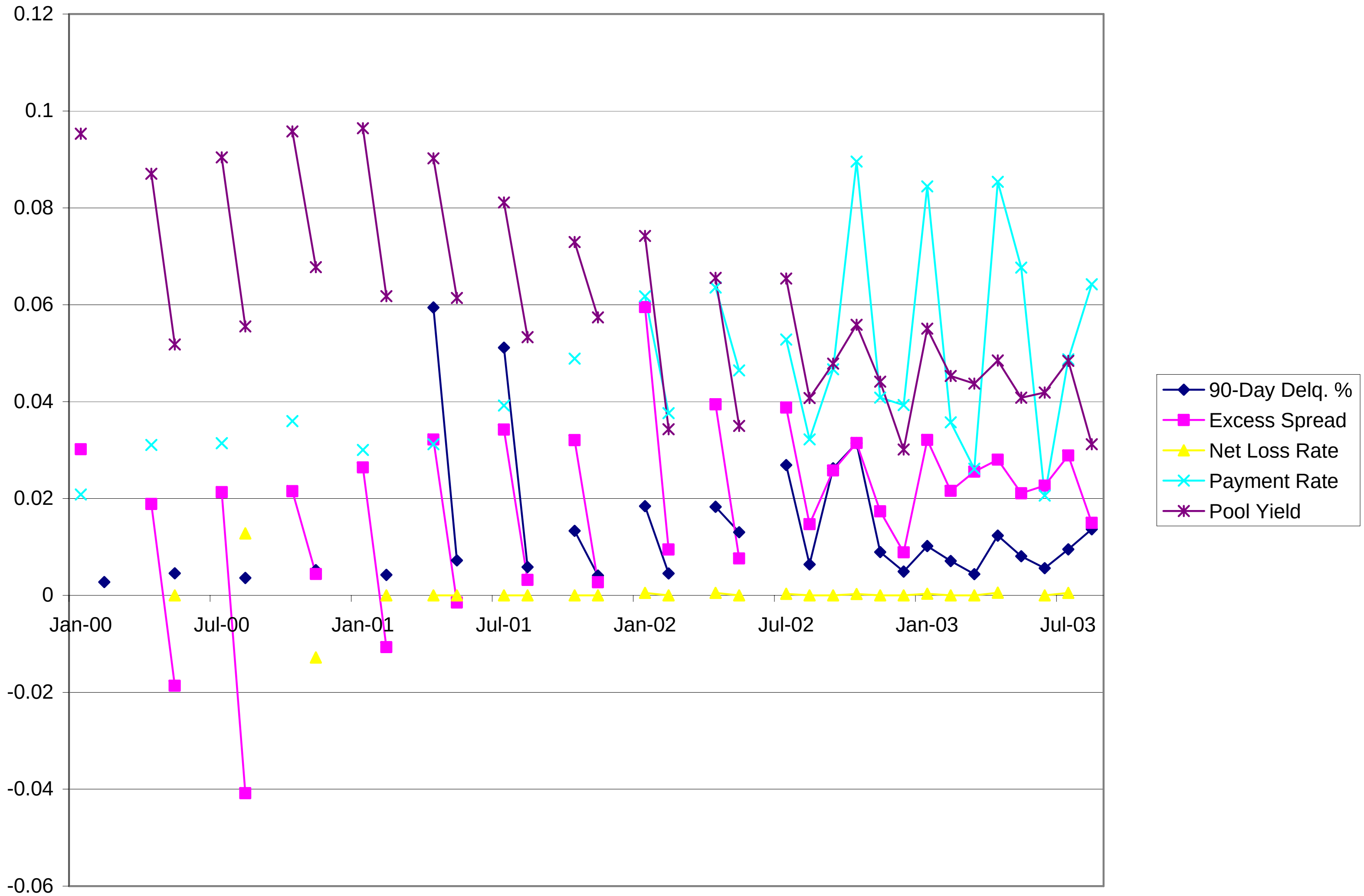
Appendix C, Figure C9
Median Performance Measures over Time for Other Consumer Loans



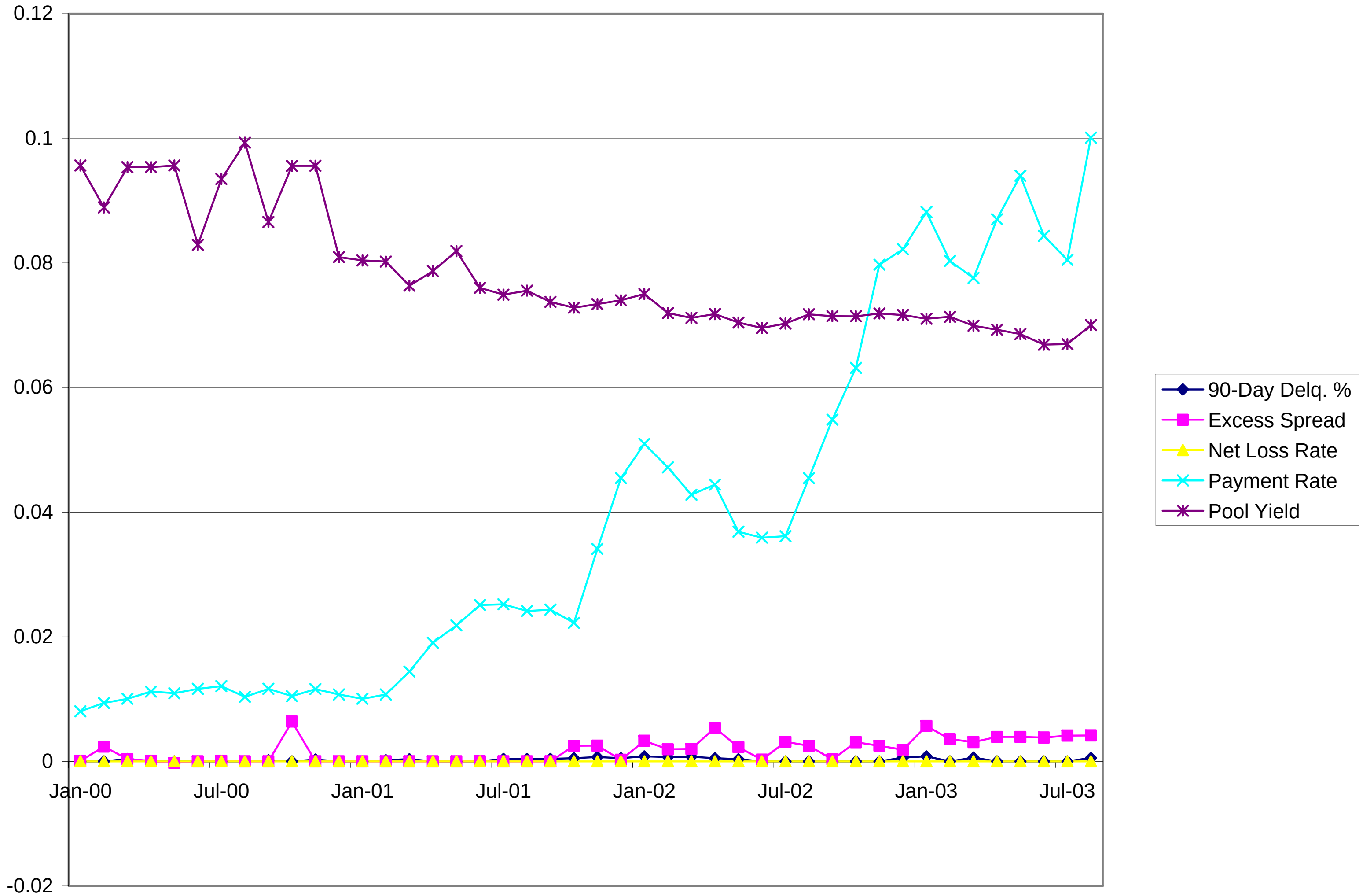
Appendix C, Figure C10
Median Performance Measures over Time for Recreational Vehicle Loans



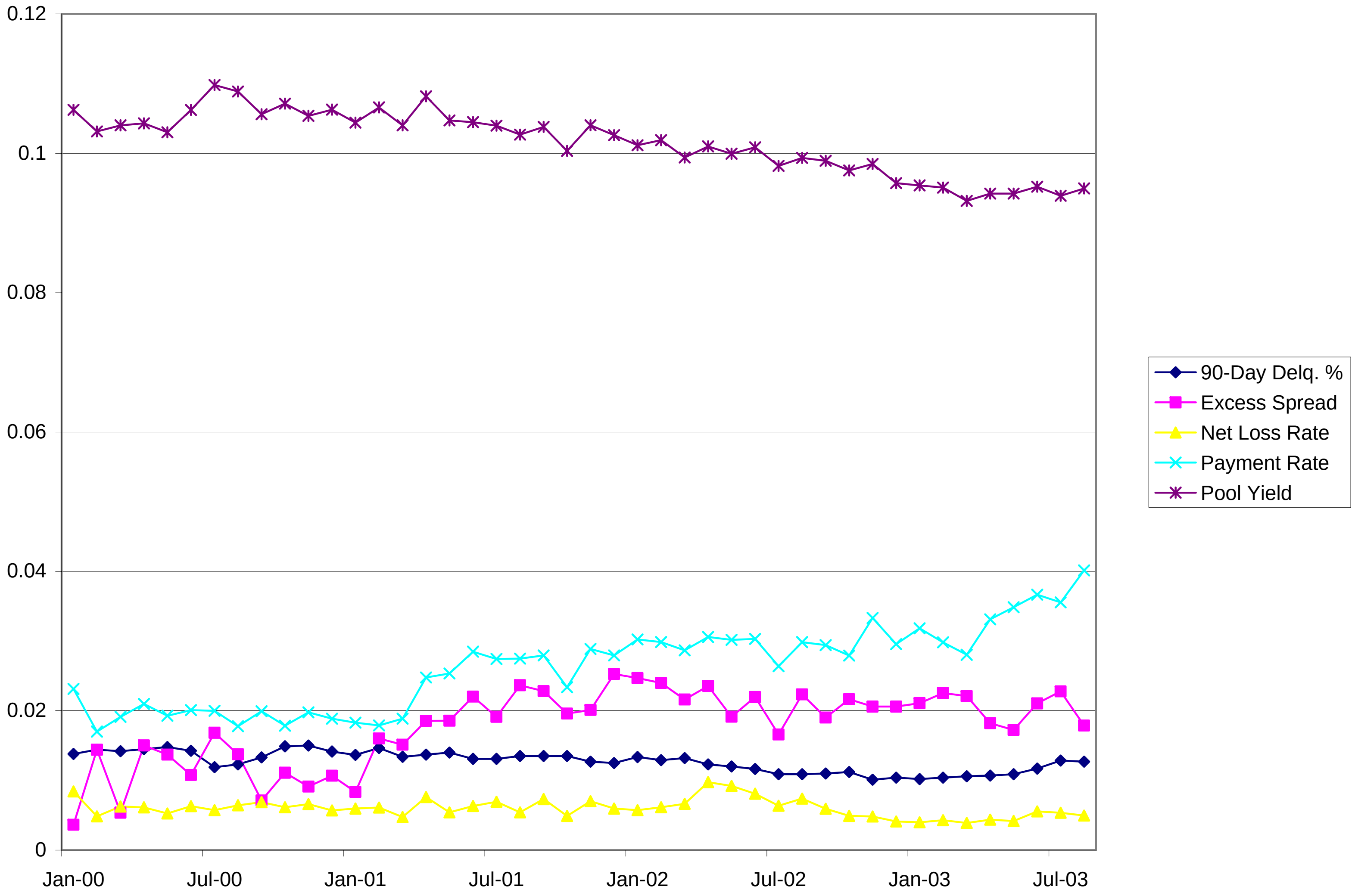
Appendix C, Figure C11
Median Performance Measures over Time for Student Loans



Appendix C, Figure C12
Median Performance Measures over Time for Residential Mortgage Loans



Appendix C, Figure C13
Median Performance Measures over Time for Home Equity Loans



Appendix D, Table D1
Sample Attrition for Pool Yield

The following table contains the sample attrition for Pool Yield for all asset categories. Pool Yield was screened for extreme observations. Any observations greater than 1.0 and less than -1.0 were assumed to be missing values. To be included in the sample, a pool in any asset class must have at least six observations for Pool Yield over the January 2000 to September 2003 time period. Duplicate observations arising due to Master Trust reporting are eliminated.

Asset Class	Original Number of Obs.	Number of Obs. Lost Due to Elimination of Duplicate Master Trust Series	Number of Extreme Obs. Replaced	Number of Obs. Lost Due to Required Obs. Size (6).	Final Number of Obs. Used in Estimation	Number of Pools
Residential Mortgages	54071	347	10	48755	4969	205
Home Equity Loans	82687	0	66	56136	26551	842
Auto Leases	416	0	17	75	341	17
Auto Loans	9794	0	13	1091	8703	335
Credit Cards	14936	5349	0	508	9079	351
Commercial Mortgages	14644	0	0	14572	72	4
Dealer Floorplan Loans	1651	449	0	66	1136	42
Equipment Leases	3169	12	14	2589	568	21
Marine and Boat Loans	412	0	0	0	412	10
Manufactured Home Loans	9466	0	26	1380	8086	213
Other Consumer Loans	1405	255	3	423	727	23
Recreational Vehicle Loans	1048	80	0	0	1048	30
Student Loans	509	0	0	126	383	29

Appendix D, Table D2
Sample Attrition for 90-day Delinquent Balance

The following table contains the sample attrition for 90-day Delinquent Balance for all asset categories. 90-day Delinquent Balance was screened for extreme observations. Any observations greater than 1.0 and less than 0.0 were assumed to be missing values. To be included in the sample, a pool in any asset class must have at least six observations for 90-day Delinquent Balance over the January 2000 to September 2003 time period. Duplicate observations arising due to Master Trust reporting are eliminated.

Asset Class	Original Number of Obs.	Number of Obs. Lost Due to Elimination of Duplicate Master Trust Series	Number of Extreme Obs. Replaced	Number of Obs. Lost Due to Required Obs. Size (6).	Final Number of Obs. Used in Estimation	Number of Pools
Residential Mortgages	54071	6619	7	6006	41446	1180
Home Equity Loans	82687	1068	5	17090	64529	1844
Auto Leases	416	0	0	94	322	14
Auto Loans	9794	0	0	2619	7175	273
Credit Cards	14936	4692	0	2871	7373	282
Commercial Mortgages	14644	4404	3	3019	7721	197
Dealer Floorplan Loans	1651	0	0	1580	71	3
Equipment Leases	3169	0	0	1147	2022	66
Marine and Boat Loans	412	44	0	0	368	9
Manufactured Home Loans	9466	0	0	784	8682	229
Other Consumer Loans	1405	255	0	402	748	22
Recreational Vehicle Loans	1048	0	0	23	1025	29
Student Loans	509	0	0	360	149	11

Appendix D, Table D3
Sample Attrition for Net Loss Rate

The following table contains the sample attrition for Net Loss Rate for all asset categories. Net Loss Rate was screened for extreme observations. Any observations greater than 1.0 and less than -1.0 were assumed to be missing values. To be included in the sample, a pool in any asset class must have at least six observations for Net Loss Rate over the January 2000 to September 2003 time period. Duplicate observations arising due to Master Trust reporting are eliminated.

Asset Class	Original Number of Obs.	Number of Obs. Lost Due to Elimination of Duplicate Master Trust Series	Number of Extreme Obs. Replaced	Number of Obs. Lost Due to Required Obs. Size (6).	Final Number of Obs. Used in Estimation	Number of Pools
Residential Mortgages	54071	12746	20	15217	26108	697
Home Equity Loans	82687	5088	184	10944	66655	1992
Auto Leases	416	0	0	114	302	14
Auto Loans	9794	18	4	599	9177	393
Credit Cards	14936	4421	0	2917	7798	303
Commercial Mortgages	14644	123	0	14391	130	5
Dealer Floorplan Loans	1651	97	0	1039	515	20
Equipment Leases	3169	59	2	959	2151	74
Marine and Boat Loans	412	0	0	0	412	10
Manufactured Home Loans	9466	179	0	1906	7381	198
Other Consumer Loans	1405	123	0	977	305	11
Recreational Vehicle Loans	1048	0	0	11	1037	29
Student Loans	509	7	0	177	325	25

Appendix D, Table D4
Sample Attrition for Payment Rate

The following table contains the sample attrition for Payment Rate for all asset categories. Payment Rate was screened for extreme observations. Any observations greater than 1.0 and less than 0.0 were assumed to be missing values. To be included in the sample, a pool in any asset class must have at least six observations for Payment Rate over the January 2000 to September 2003 time period. Duplicate observations arising due to Master Trust reporting are eliminated.

Asset Class	Original Number of Obs.	Number of Obs. Lost Due to Elimination of Duplicate Master Trust Series	Number of Extreme Obs. Replaced	Number of Obs. Lost Due to Required Obs. Size (6).	Final Number of Obs. Used in Estimation	Number of Pools
Residential Mortgages	54071	708	228	15216	38147	1081
Home Equity Loans	82687	227	212	15666	66794	1974
Auto Leases	416	0	0	26	390	19
Auto Loans	9794	0	0	1099	8695	335
Credit Cards	14936	5349	13	532	9055	349
Commercial Mortgages	14644	0	0	14350	294	10
Dealer Floorplan Loans	1651	449	0	27	1175	44
Equipment Leases	3169	12	1	2403	754	26
Marine and Boat Loans	412	0	0	0	412	10
Manufactured Home Loans	9466	0	6	134	9332	245
Other Consumer Loans	1405	123	19	555	727	23
Recreational Vehicle Loans	1048	0	1	0	1048	30
Student Loans	509	0	1	153	356	27

Appendix D, Table D5
Sample Attrition for Excess Spread

The following table contains the sample attrition for Excess Spread for all asset categories. Excess Spread was screened for extreme observations. Any observations greater than 1.0 and less than -1.0 were assumed to be missing values. To be included in the sample, a pool in any asset class must have at least six observations for Excess Spread over the January 2000 to September 2003 time period. Duplicate observations arising due to Master Trust reporting are eliminated.

Asset Class	Original Number of Obs.	Number of Obs. Lost Due to Elimination of Duplicate Master Trust Series	Number of Extreme Obs. Replaced	Number of Obs. Lost Due to Required Obs. Size (6).	Final Number of Obs. Used in Estimation	Number of Pools
Residential Mortgages	54071	320	3	50357	3394	146
Home Equity Loans	82687	361	109	57201	25107	788
Auto Leases	416	0	18	134	282	14
Auto Loans	9794	0	7	1115	8679	333
Credit Cards	14936	833	0	756	13347	450
Commercial Mortgages	14644	0	0	14644	0	0
Dealer Floorplan Loans	1651	0	0	159	1492	52
Equipment Leases	3169	12	5	2884	273	12
Marine and Boat Loans	412	0	0	0	412	10
Manufactured Home Loans	9466	0	3	1470	7996	208
Other Consumer Loans	1405	0	2	799	606	18
Recreational Vehicle Loans	1048	0	0	0	1048	30
Student Loans	509	0	3	126	383	29

Appendix E, Table E1
Estimation of Pool Yield Correlations across Basel Asset Categories

The following table contains the Pearson product-moment correlation of Pool Yields across the Basel asset categories. Monthly mean values over the time period from January 2000 to September 2003 for Pool Yield are obtained by finding the least squared mean values. Least squared mean values are found by estimating equation (1), *Y=f(pool, time)* for each Basel asset category where Y is the Pool Yield. To be included in the analysis a pool must have at least six valid observations for Pool Yield over the January 2000 to September 2003 time period. Extreme observations are eliminated from the analysis. An asterisk indicates that the correlation is significantly different from zero at the 5% level.

	Residential with Home Equity Loans	Residential without Home Equity Loans	Other Retail Credit	Credit Cards (Qualifying Revolving)	Home Equity Loans
Residential with Home Equity Loans	1.000				
Residential without Home Equity Loans	0.0111	1.000			
Other Retail Credit	0.3728*	0.1029	1.000		
Credit Cards (Qualifying Revolving)	0.1172	-0.5166*	-0.2827	1.000	
Home Equity Loans	0.8376*	-0.0778	0.3134*	-0.0870	1.000

Appendix E, Table E2
Estimation of 90-day Delinquent Balance Correlations across Basel Asset Categories

The following table contains the Pearson product-moment correlation of 90-day Delinquent Balances across the Basel asset categories. Monthly mean values over the time period from January 2000 to September 2003 for 90-day Delinquent Balance are obtained by finding the least squared mean values.

Least squared mean values are found by estimating equation (1), *Y=f(pool, time)* for each Basel asset category where Y is the 90-day Delinquent Balance. To be included in the analysis a pool must have at least six valid observations for 90-day Delinquent Balance over the January 2000 to September 2003 time period. Extreme observations are eliminated from the analysis. An asterisk indicates that the correlation is significantly different from zero at the 5% level.

	Residential with Home Equity Loans	Residential without Home Equity Loans	Other Retail Credit	Credit Cards (Qualifying Revolving)	Home Equity Loans
Residential with Home Equity Loans	1.000				
Residential without Home Equity Loans	0.9401*	1.000			
Other Retail Credit	0.9646*	0.9225*	1.000		
Credit Cards (Qualifying Revolving)	0.6751*	0.6292*	0.6946*	1.000	
Home Equity Loans	0.2170	0.2702	0.2807	0.0099	1.000

Appendix E, Table E3
Estimation of Net Loss Rate Correlations across Basel Asset Categories

The following table contains the Pearson product-moment correlation of Net Loss Rates across the Basel asset categories. Monthly mean values over the time period from January 2000 to September 2003 for Net Loss Rate are obtained by finding the least squared mean values. Least squared mean values are found by estimating equation (1), *Y=f(pool, time)* for each Basel asset category where Y is the Net Loss Rate. To be included in the analysis a pool must have at least six valid observations for Net Loss Rate over the January 2000 to September 2003 time period. Extreme observations are eliminated from the analysis. An asterisk indicates that the correlation is significantly different from zero at the 5% level.

	Residential with Home Equity Loans	Residential without Home Equity Loans	Other Retail Credit	Credit Cards (Qualifying Revolving)	Home Equity Loans
Residential with Home Equity Loans	1.000				
Residential without Home Equity Loans	0.5881*	1.000			
Other Retail Credit	0.7249*	0.4618*	1.000		
Credit Cards (Qualifying Revolving)	0.8378*	0.4379*	0.7721*	1.000	
Home Equity Loans	0.9385*	0.4436*	0.5068*	0.7429*	1.000

Appendix E, Table E4
Estimation of Payment Rate Correlations across Basel Asset Categories

The following table contains the Pearson product-moment correlation of Payment Rates across the Basel asset categories. Monthly mean values over the time period from January 2000 to September 2003 for Payment Rate are obtained by finding the least squared mean values. Least squared mean values are found by estimating equation (1), *Y=f(pool, time)* for each Basel asset category where Y is the Payment Rate. To be included in the analysis a pool must have at least six valid observations for Payment Rate over the January 2000 to September 2003 time period. Extreme observations are eliminated from the analysis. An asterisk indicates that the correlation is significantly different from zero at the 5% level.

	Residential with Home Equity Loans	Residential without Home Equity Loans	Other Retail Credit	Credit Cards (Qualifying Revolving)	Home Equity Loans
Residential with Home Equity Loans	1.000				
Residential without Home Equity Loans	0.9912*	1.000			
Other Retail Credit	0.7705*	0.7490*	1.000		
Credit Cards (Qualifying Revolving)	0.4967*	0.4740*	0.5338*	1.000	
Home Equity Loans	0.8683*	0.8228*	0.5617*	0.3821*	1.000

Appendix E, Table E5
Estimation of Excess Spread Correlations across Basel Asset Categories

The following table contains the Pearson product-moment correlation of Excess Spreads across the Basel asset categories. Monthly mean values over the time period from January 2000 to September 2003 for Excess Spread are obtained by finding the least squared mean values. Least squared mean values are found by estimating equation (1), *Y=f(pool, time)* for each Basel asset category where Y is the Excess Spread. To be included in the analysis a pool must have at least six valid observations for Excess Spread over the January 2000 to September 2003 time period. Extreme observations are eliminated from the analysis. An asterisk indicates that the correlation is significantly different from zero at the 5% level.

	Residential with Home Equity Loans	Residential without Home Equity Loans	Other Retail Credit	Credit Cards (Qualifying Revolving)	Home Equity Loans
Residential with Home Equity Loans	1.000				
Residential without Home Equity Loans	0.2483	1.000			
Other Retail Credit	-0.2697	-0.2241	1.000		
Credit Cards (Qualifying Revolving)	0.6070*	0.3114*	-0.0523	1.000	
Home Equity Loans	0.8875*	0.0353	-0.3283*	0.3467*	1.000