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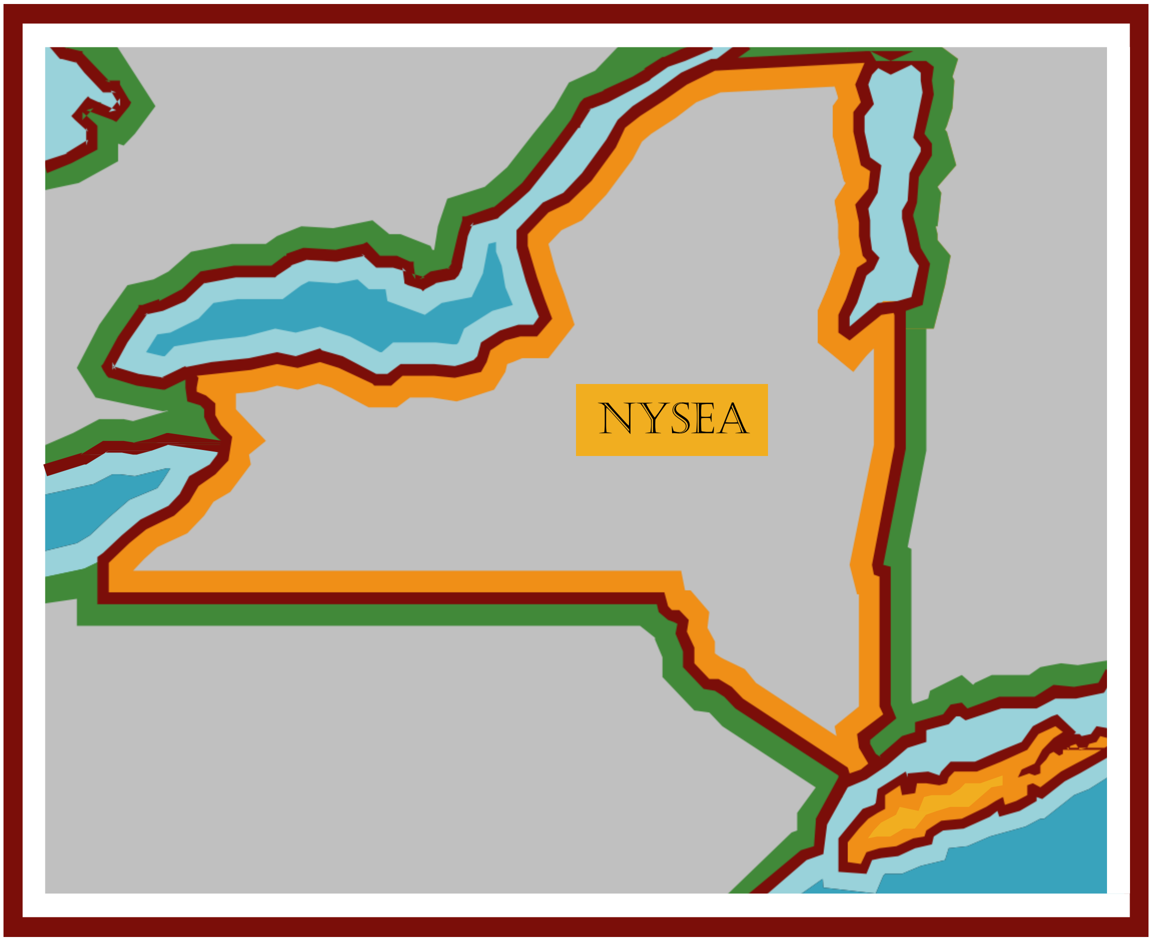

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ARTICLES

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Tail Dependence between Stock Index Returns and Foreign Exchange Rate Returns− a Copula Approach

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ABSTRACT

This study estimates the tail dependence between stock index returns and foreign exchange rate returns for four East Asian countries. We apply the concept of a copula to model the dependence structure, especially in the tail area, between the two returns series for each country under examination. Our major findings are that for the more advanced country (Singapore), there exists neither lower nor upper tail dependence between stock index returns and exchange rate returns for the sample period. For the three emerging markets, Indonesia and South Korea have much stronger lower tail dependency than upper tail, indicating a higher probability of double losses than double gains. Taiwan has symmetric tail dependence with similar lower and upper tail coefficients. Our findings have important implications for international diversification and market risk management.

INTRODUCTION

Understanding the dependence between risk factors is crucial in risk management and asset allocation. This study aims to examine the tail dependence between the stock index returns and exchange rate returns of four East Asian countries: Indonesia, South Korea, Singapore, and Taiwan. Tail behavior of random variables during extreme events, such as a financial crisis, can be captured via measures of tail dependence. In our case, tail dependence measures the probability that we will observe an extremely large gain in the stock market, given that the local currency also has had a large appreciation against the USD. For a U.S. investor seeking international diversification, he/she will experience double large gains, one in the equity market, and the other in the currency market when translating the local currency investment into U.S. dollars. Likewise, when the stock market crashes, the foreign investor not only loses big in the stock market, but also in the currency market. Therefore, the goal of risk reduction cannot be achieved due to this possibility.

The questions we endeavor to answer in this study are: 1) is there any tail dependency between equity returns and currency returns? If we find positive tail dependence between the two markets, U.S. investors' investments in the East Asian equity markets will more likely experience extreme double losses and extreme double gains; 2) Is the tail dependency similar for the countries?; 3) Do the tails exhibit symmetric or asymmetric dependency in that economic region? By answering these questions we hope to better understand the co-movements of equity-currency markets for the selected countries in this economic region.

Extensive research has been done on the relationship between these two markets, both theoretically and empirically. On the theoretical side, there are two models explaining the causal relationship between the equity and currency markets. One is the "stock oriented"[1] model of exchange

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rate determination and the other is the “flow-oriented”[2] model. From the microeconomic point of view, local currency appreciation can place exporting firms at a competitive disadvantage, thereby lowering their stock prices, indicating a negative relationship between stock returns and the exchange rate. On the other hand, importing firms can benefit from home currency appreciation, suggesting a positive relationship between these two markets. From the macroeconomic point of view, if the domestic interest rate is high relative to the rest of the world, the higher demand for home currency leads to its appreciation. In the meantime, higher interest rates also increase domestic firms’ borrowing cost, causing lower stock prices. This suggests a negative relationship between these two markets. Mixed results have been documented on the causal relationship between these two markets. Using ordinary least squares (OLS) estimation, Solnik (1987) finds a weak positive relationship for monthly data but a negative relationship for quarterly data for eight western markets. Using an error correction model (ECM), Ajayi and Mougoue (1996) find that, in the short run, the relationship between stock prices and the home currency is negative, but positive in the long run. Using a GARCH approach, Patro et al. (2002) find significant currency risk exposure in country equity index returns for 16 OECD countries. Using a Granger causality test, Pan et al. (2007) study the dynamic linkages between exchange rates and stock prices for several East Asian countries. They find a significant causal relationship from exchange rates to stock prices before the 1997 Asian financial crises.

The conventional dependence measure is constructed as an average of deviations from the mean and it doesn’t distinguish between large or small realizations or between positive and negative returns. And it is based on assumptions of a linear relationship and a multivariate Gaussian distribution. Since the research of Embrechts et al. (2002) identified the limitations of correlation-based models in risk management, the copula method has become a more popular approach in modeling the dependence structure between financial variables. Copulas can capture dependence throughout the entire distribution of asset returns, independent of the univariate returns distribution. Not only can copulas model the degree of dependence, but also the structure of dependence. Works on the dependence structure across international equity markets using copulas include Mashal and Zeevi (2002), Hu (2006), Chollete et al. (2006, 2009), and Rodriguez (2007). Patton (2006) examines the dependence structure on currency markets, and Ning (2010) looks at the dependence between equity and currency markets.

This study is similar to the previous literature in the sense that it also models dependence in international financial market returns. It is different from the existing works and contributes to the literature in the following ways: first, the countries and data period are different; secondly, this paper studies the degree of tail dependence using unconditional copulas as well as conditional copulas. Our key empirical result reveals that the tail dependence coefficient is significant for the three East Asian emerging markets (asymmetric tail dependence for Indonesia and South Korea and symmetric tail dependence for Taiwan), but for Singapore, there isn’t enough evidence to support the existence of any tail dependency between foreign exchange rate returns and stock index returns. Our findings have important implications in risk management and asset pricing. For global investors seeking to diversify their portfolio into emerging markets, ignoring the joint downside risk would underestimate the value-at-risk (VaR), which is a common market risk measure in risk management practice. Our finding should also affect the pricing of assets. As pointed out by Phylaktis and Ravazzolo (2004), an international capital asset pricing model (ICAPM) will be mis-specified if currency risk[3] is omitted. Poon et al. (2004) states that tail dependence is a true measure for systematic risk in times of financial crisis and global investors should be compensated for exposure to such risk during joint market downturns.

The remainder of this paper is organized as follows. Section II introduces copula concepts and measures of tail dependence. Section III specifies the models and estimation method. In section IV, we describe the data used and present the empirical evidence of extreme co-movements. We offer concluding remarks in section V.

DEPENDENCE MEASURES AND COPULA[4] CONCEPTS

In finance, the most popular measure of dependence is linear correlation. Under the assumption of a multivariate normal distribution, the linear correlation is the canonical measure of dependence. However empirical evidence in finance has proved the inadequacy of the multivariate normal distribution. Therefore, linear correlation as a measure of dependence can often lead to misleading results. As an alternative, co-movement between financial markets and risk factors can be modeled in a flexible way by the copula method. In this section, after providing a brief review of the classical measures of dependence we introduce the general concept of copulas and how copulas are used to model tail dependence in the finance literature.

Classical measures of dependence

Linear correlation

Linear correlation is the most popular measure of dependence, and it is also known as Pearson's product moment correlation. The linear correlation coefficient between two random variables of X and Y (ρ (X, Y)) lies between the values of −1 and 1. If ρ (X, Y) = 1, we say that X and Y are perfectly positively correlated. In the case of ρ (X, Y) = −1, X and Y are perfectly negatively correlated. The value of 0 indicates that there is no linear correlation between X and Y. As explained by Embrechts et al. (2002), the linear correlation is a dependence measure only in the case of multivariate normal distributions.

Rank correlation

There are two non-parametric measures of correlation, Kendall's tau and Spearman's rho. Kendall's tau and Spearman's rho are bivariate measures of dependence and they both provide distribution free measures of dependence between two variables that are known as concordance measures of dependence. Kendall's tau and Spearman's rho coefficients lie inside the interval [−1, 1]. The value of −1 indicates that the disagreement between the two rankings is perfect. The value of 0 indicates the rankings are completely independent, and if the agreement between the two rankings is perfect, the rank coefficient is +1. Concordance correlation measures like Kendall's tau and Spearman's rho are independent of the univariate marginal distributions. They provide the best alternatives to the linear correlation coefficient as a measure of dependence for non-elliptical distributions. The advantage of rank correlations over linear correlation is that they are invariant under monotonic transformations.

Copula measures of dependence

Dependence between random variables can also be modeled by the copula (coined by Sklar (1959)) method, an increasingly popular way to model the dependence between financial risk factors. As described in Joe (1997), a copula is a multivariate distribution function that is used to bind each marginal distribution function to form the joint distribution function. Copulas parameterize the dependence between the margins, while the parameters of each marginal distribution function can be estimated separately.

The advantages of the copula method over traditional methods to measure dependence are as follows. One is that copulas allow modeling a nonlinear dependence structure. The second is that no assumption is required regarding the marginal distribution, which is particularly suitable for financial returns data, as there is no known exact distribution. Third, we can use copulas to model tail events, which can never be over-emphasized in financial risk management practice.

Sklar's Theorem and Copulas

The theorem central to the theory of copulas is called Sklar's theorem. In 1959, Sklar (1959) created a new class of functions now known as copulas, which couple a joint distribution function to its univariate marginals. We will present this theorem mainly by following Nelson (1999).

Sklar's Theorem[5] (Sklar, 1959). *Let H be a joint distribution function with marginals F and G. then there exists a copula C such that for all x, y in R,*

(1) $$H(x, y) = C(F(x), G(y)).$$

If F and G are continuous, then C is unique; otherwise, C is uniquely determined on RanF×RanG*. Conversely, if C is a copula and F and G are distribution functions, then the function H defined by the above equation is a joint distribution function with marginals F and G.*

Definition 1 A two-dimensional copula is a function C: $[0, 1]^2 \rightarrow [0, 1]$ which satisfies the following properties:

(a) Grounded: for every u, v in [0, 1], $C(u, 0) = 0 = C(0, v)$;

(b) $C(u,1) = u$ and $C(1, v) = v$ for all (u, v)

(c) 2-increasing: for every u_1, u_2, v_1, v_2 in [0, 1] such that $u_1 \le u_2$ and $v_1 \le v_2$,

$$C(u_2, v_2) - C(u_2, v_1) - C(u_1, v_2) + C(u_1, v_1) \ge 0.$$

Hence, any bivariate distribution function whose margins are standard uniform distributions is a copula. From the definition, we know that copulas are joint distribution functions of standard uniform random variables:

$$C(u, v) = \Pr(U_1 \le u, U_2 \le v)$$

The following probabilities of uniform variates can be written via copulas:

$$\Pr(U_1 \le u, U_2 > v) = u - C(u, v)$$
$$\Pr(U_1 > u, U_2 \le v) = v - C(u, v)$$
$$\Pr(U_1 \le u \,|U_2 \le v) = C(u, v) / 2$$
$$\Pr(U_1 \le u \,|U_2 > v) = \ .\frac{1-2u+C(u,u)}{1-u}$$

For a more detailed treatment of copulas, the reader can refer to Joe (1997) and Nelson (1999). For an overview of copula applications in finance, see Cherubini et al. (2004) and Patton (2009) for copula applications in financial time series.

Measure of tail dependence[6]

Tail dependence refers to the amount of dependence in the tails of a bivariate distribution or alternatively the dependence in the corner of the lower-left quadrant or upper-right quadrant of a bivariate distribution. Tail dependence between two random variables is a copula property and hence the amount of tail dependence is invariant under strictly increasing transformations of X and Y. For two random variables X and Y with marginal distributions $F_X(x)$ and $F_Y(y)$, the upper tail dependence is

(2) $$\lambda_r = \lim_{u\to 1} \Pr[F_Y(y) \geq u | F_X(x) \geq u] = \lim_{u\to 1} \frac{1-2u+C(u,u)}{1-u}$$

and the lower tail dependence is

(3) $$\lambda_l = \lim_{u\to 0} \Pr[F_Y(y) \leq u \mid F_X(x) \leq u] = \lim_{u\to 0} \frac{C(u,u)}{u}$$

where λ_r and $\lambda_l \in [0,1]$. Positive λ_l or λ_r indicates that X and Y are tail dependent. If the tail dependence coefficient is zero, the variables are asymptotically independent. However, tail independence does not mean that the variables are independent. Copulas with the different tail dependence structure applied in this study are introduced in the next section.

ESTIMATION METHOD AND MODEL SPECIFICATION

Generally speaking, there are two approaches to estimate copula models, one is the one-stage full maximum likelihood estimation method, and the other is the two- stage inference functions for margins (IFM) method proposed by Joe and Xu (1996). The one-stage approach estimates the parameters of the marginal models and the parameters of the copula models simultaneously. Given the large number of parameters, this method can be computationally intensive and makes the numerical maximization of the log likelihood function difficult. Therefore, in practice, the two-stage IFM method is preferred due to its computational tractability. Under the IFM approach, the first step models the marginal models, either parametrically or non-parametrically. If estimation is done non-parametrically, then the method is a semi-parametric two-step estimation method, also known as the Canonical Maximum Likelihood, or CML method. Copula parameters are estimated in the second step. For more details on this estimation method, the interested reader can refer to Cherubini et al. (2004). Joe (1997) points out that the IFM is a highly efficient method, and he proves that the IFM estimator is consistent and asymptotically normal under standard conditions[7].

The marginal models

We model the marginal distributions parametrically using GARCH type models. In the finance literature, a very common approach to model time series is the generalized autoregressive conditional heteroskedasticity (GARCH) model. In particular, we filter the raw returns data with AR(*k*)-GARCH(*p*, *q*) or AR(*k*)-*t*-GARCH(*p*, *q*) type models. This type of model has been used in Bollerslev (1987), Patton (2006), and Ning (2010) among others. The marginal model is specified as follows:

(4) $$r_{i,t} = C_i + \sum_k AR_{i,t-k} \times r_{i,t-k} + \varepsilon_{i,t}$$

(5) $$\sigma_{i,t}^2 = Arch0_i + \sum_p Garch\,(p)_i \times \sigma_{i,t-p}^{\;2} + \sum_q Arch\,(q)_i \times \varepsilon_{i,t-q}^{\;2}$$

where $r_{i,t}$ is the returns for country *i* at time *t*, $\sigma_{i,t}^2$ is the variance of $\varepsilon_{i,t-}$ term in the mean equation (4). Estimation results of the marginal model are discussed in the next section.

Static copula models

Student's t-copula

The Student's t- copula is based on the multivariate t distribution, in the same way as the Gaussian copula is derived from the multivariate normal distribution. The copula of the bivariate Student's t-distribution with a degrees of freedom of *v* and correlation *ρ* is:

(6) $$C^{t}_{v,\rho}(u,v) = \int_{-\infty}^{t_v^{-1}(u)} \int_{-\infty}^{t_v^{-1}(v)} \frac{1}{2\pi\sqrt{1-\rho^2}} \left\{1 + \frac{(s^2+t^2-2\rho st)}{v(1-\rho^2)}\right\}^{-(v+2)/2} dsdt\ .$$

As the value of *v* increases, say *v* = 100, it approximates a Gaussian distribution. The bivariate Student's t-copula exhibits symmetric tail dependence and has the tail independence Gaussian copula as a special case.

Clayton copula

The Clayton copula belongs to the Archimedean Copula family and is known to have left tail dependence. The bivariate Clayton copula can be written as:

(7) $$C_{\theta}^{Cl}(u,v) = (u^{-\theta} + v^{-\theta} - 1)^{-\frac{1}{\theta}}$$

where 0<θ<∞ is a parameter controlling the dependence, θ→0+ implies independence, and implies perfect dependence. *u* and *v* are standard uniformly distributed i.i.ds. The Clayton copula can be used to describe lower tail dependence and no upper tail dependence.

Symmetrized Joe-Clayton copula (SJC)

The Symmetrized Joe-Clayton (SJC) copula allows both upper and lower tail dependence and symmetric dependence as a special case. The SJC copula is a modified version of the Joe-Clayton copula (Joe, 1997), as proposed by Patton (2006) and is defined as follows:

(8) $$C_{SJC}(u,v|\lambda_r,\lambda_l) = 0.5 \cdot \left(C_{JC}(u,v|\lambda_r,\lambda_l) + C_{JC}(1-u,1-v|\lambda_r,\lambda_l) + u + v - 1\right)$$

where $C_{JC}(u, v|\lambda_r, \lambda_l)$ is the Joe-Clayton copula defined as follows

(9) $$C_{JC}(u,v|\lambda_r,\lambda_l) = 1 - \left(1 - \{[1-(1-u)^k]^{-\gamma} + [1-(1-v)^k]^{-\gamma} - 1\}^{-1/\gamma}\right)^{1/k}$$

where $k = 1/\log_2(2 - \lambda_r)$, $\gamma = -1/\log_2(\lambda_l)$, and $\lambda_r(0,1)$, $\lambda_l(0,1)$. As pointed out in Patton (2006), the main drawback with the Joe-Clayton copula is that, even when λ_l and λ_r are equal, there is still slight asymmetry in the copula. Given the way the SJC copula is constructed, it is a better copula model to determine the presence or absence of asymmetry based on the empirical tail dependence measures. We discuss our empirical results based on SJC copula model.

Dynamic copula model[8]

To examine time-varying tail dependence in the returns series, we use the time-varying SJC copula, as proposed in Patton (2006).

(10) $$\lambda t = \Lambda\left(\omega + \beta\lambda_{t-1} + \alpha \cdot \frac{1}{10}\sum_{i=1}^{10}|u_{t-i} - v_{t-i}|\right)$$

where Λ denotes the logistic transformation to keep the tail dependency parameter of the SJC copula in [0,1] and is defined as $\Lambda(x) = (1 + e^{-x})^{-1}$.

The dynamic copula model contains an autoregressive term designed to capture persistence in dependence and a forcing variable which is the mean absolute difference between *u* and *v*. The forcing variable is positive when the two probability integral transforms are on the opposite side of the extremes of the joint distribution and close to zero when they are on the same side of the extremes.

DATA AND EMPIRICAL RESULTS

Data

The dataset used in this study consists of daily closing stock index returns and foreign exchange rate movements for four East Asian countries (Indonesia, South Korea, Singapore, and Taiwan). The stock indices are the Jakarta SE Composite Index of Indonesia, the Korea Stock Exchange Stock

Price Index (KOSPI), The Singapore Strait Times Stock Exchange, and the Taiwan Stock Exchange Capitalization Weighted Index[9]. The corresponding exchange rates are Indonesia rupiah (US$/IDR), Korean won (US$/KRW), Singapore dollar (US$/SGD), and Taiwanese dollar (US$/TWD). The sample period was from July 3, 1997 to June 4, 2010[10]. The stock index returns are computed as

$$r_{i,t} = 100 \times \ln(\frac{P_{i,t}}{P_{i,t-1}}). \quad (11)$$

where $P_{i,t}$ is the stock index level at time t for country i and $P_{i,t-1}$ is the stock index level at time $t-1$ for country i. The foreign exchange rate returns are computed as

$$e_{i,t} = 100 \times \ln(\frac{S_{i,t}}{S_{i,t-1}}). \quad (12)$$

where $S_{i,t}$ is the spot exchange rate at time t for currency i, and $S_{i,t-1}$ is the spot exchange rate level at time t-1 for country i, expressed as units of USD per unit of local currency.

Table 1 Summary Statistics (percent)

Country	Indonesia	Korea	Singapore	Taiwan
Panel A: Stock index returns				
No. of observations	3034	3074	3155	3066
Mean	0.0446	0.0248	0.0112	-0.0066
Std. dev.	1.8707	2.1706	1.5206	1.6898
Min	-12.7318	-12.8047	-9.2155	-9.9360
Max	13.1278	12.0583	12.8738	8.5198
Skewness	-0.0749	-0.0970	0.0346	-0.1416
Kurtosis	8.9916	6.6713	9.6166	5.3880
J-B stat	4541.12**	1731.18**	5755.83**	738.74**
LB(20)	131.64**	43.66**	58.61**	36.73*
$LB^2(20)$	999.86**	1631.96**	1505.41**	674.35**
Panel B: Currency returns				
Mean	-0.0436	-0.0099	0.0004	-0.0048
Std. dev.	1.9711	1.0490	0.4064	0.3230
Min	-30.1880	-13.4437	-2.7168	-3.3971
Max	23.3162	10.9970	4.0448	3.3647
Skewness	-1.4193	-0.9425	0.7672	-0.4944
Kurtosis	53.5803	40.6763	15.2315	21.0622
J-B stat	324438.89**	182269.36**	19976.97**	41802.28**
LB(20)	144.01**	434.04**	77.36**	81.13**
$LB^2(20)$	2905.22**	4878.54**	1960.91**	412.07**

Note: ** significant at 1 percent level; * significant at 5 percent level.

Table 1 presents summary statistics of the daily stock index returns and foreign exchange rate returns for each country, and all returns are in percentage terms. As seen in the table, East Asian equity markets (with the exception of Taiwan for the sample period) did provide higher returns than the S&P 500[11] but at the expense of higher risk, as measured by the sample standard deviation. Generally, the standard deviation of stock index returns is higher than that of currency movements, with the exception of Indonesia. On average, the Indonesian rupiah, South Korean won, and Taiwanese dollar depreciated against the U.S. dollar. The negative skewness measure of the stock index returns and foreign exchange rate returns (with the exception of Singapore) means that the returns distributions have long left tails. Singapore has more positive observations than negative observations in both the equity market and the currency market, as indicated by the positive measure of its skewness. The kurtosis measure for the foreign exchange rate returns (ranging from 15.8 (Singapore) to 53.6 (Indonesia)) is generally higher than that of the equity returns (ranging from 5.4 (Taiwan) to 9.6 (Singapore)). The nonzero skewness measure and excess kurtosis all point to the non-normality of the returns. The Jarque-Bera tests further confirm the non-normality of the returns data (the Jarque-Bera test strongly rejects the normality of the returns, with a p-value of smaller than 0.001 for all the stock index returns and foreign exchange rate returns). The Jarque-Bera test is based on both skewness and excess kurtosis and follows a chi-square distribution with two degrees of freedom.

We check for serial correlation with the Ljung-Box statistics. The Ljung-Box statistic on 20 lags for the raw returns is significant for all cases, implying serial dependencies in these returns. For squared returns, the Ljung-Box statistic is also significant for all cases, showing significant evidence in support of GARCH effects. All of these test statistics further confirm non-normality in the return series and the volatility clustering observed in most stock and foreign exchange markets. We employ GARCH models which are well known to capture this property in the return series.

Pearson's linear correlation, the Kendall's tau, and Spearman's rho rank correlation coefficients, which are different unconditional correlation measures, are presented in Table 2. The correlation coefficients measure the degree of dependence between the stock index returns and foreign exchange rate returns for the selected countries. The correlation coefficients observed for the three emerging markets range from 0.2107 (Indonesia) to 0.3373 (South Korea) and indicate that an increase (decrease) of the local stock market is associated with appreciation (depreciation) of the local currency, a hallmark of emerging market finance. Correlation coefficients between the two financial market returns (stock index and exchange rate) for the more advanced economy (Singapore) are lower. We also observe that the dependence is strongest in Korea, and weakest in Singapore.

Table 2 Correlation Measures

Pairs	Pearson's rho	Kendall's tau	Spearman's rho
Indonesia	0.2107	0.1408	0.2032
Korea	**0.3373**	**0.1956**	**0.2823**
Singapore	0.1486	0.0677	0.0996
Taiwan	0.2422	0.1610	0.2388

Note: this table presents different correlation measures for stock index-exchange rate return pair.

To see the dependence structure from our data, we also calculate the empirical copula for the country pairs (Knight et al., 2005). We first rank the pair of the returns series in ascending order and each series is divided evenly into 10 bins. Bin one includes the observations with the lowest values (in the lowest 10th percentile) and Bin ten includes observations in the top 10th percentile. The resulting table will show us how the two returns series are associated with each other. If the two series are perfectly positively related, we expect all the observations to lie on the major diagonal. If they are negatively related, most observations should lie in the cells on the diagonal connecting the lower-left corner and upper-right corner. If there is positive upper tail dependence, the number of observations in cell (10, 10) would be larger. We would expect a large number in cell (1, 1) if there exists positive lower tail dependence.

The empirical copula frequency counts for the four country pairs are presented in Table 3. For the Indonesia pair, cell (1, 1) (upper left corner) is 80, indicating that, out of 3034 observations, there are

80 occurrences when both the stock index returns and the exchange rate returns lie in their respective lowest 10th percentile. Cell (10, 10) (lower right corner) for the same pair is 68, meaning 68 occurrences lie in their respective top 10th percentiles. 80 and 68 in the two cells represent about 2.63 percent and 2.24 percent of the total observations respectively. Numbers in the rest of the cells are much smaller than those in these two cells, indicating both upper and lower tail dependence between these two returns series. Comparing cell (1, 1) and cell (10, 10) of all country pairs, we observe that both upper tail and lower tail dependence are present for the sample period with a higher percentage of observations lying in the lower tail area.

Table 3 Empirical Copula Results

Indonesia										**Korea**									
80	51	33	21	19	16	15	12	19	37	**97**	59	31	22	22	11	14	16	14	21
49	37	33	43	28	31	26	17	23	17	44	47	42	31	29	25	20	28	22	20
28	28	37	33	35	22	29	36	36	19	30	39	32	42	33	43	22	30	24	12
25	26	34	28	30	45	37	30	28	21	28	35	41	32	34	29	32	25	34	18
19	33	34	31	36	38	35	37	26	14	15	30	26	29	39	39	33	41	30	25
27	27	29	35	33	38	34	34	29	17	21	23	32	29	28	38	35	43	27	31
21	23	37	29	36	26	41	28	35	28	12	21	28	30	43	39	37	40	36	22
17	24	15	30	32	38	33	41	38	35	21	13	28	43	30	33	34	30	40	35
11	26	28	28	33	25	25	45	36	47	15	28	29	31	30	21	41	29	42	42
26	29	23	26	21	24	29	23	34	**68**	24	13	18	19	19	29	40	25	39	**81**
71	53	32	24	25	21	21	22	23	23	**68**	37	42	25	24	36	22	19	16	18
37	32	44	34	25	32	32	27	22	31	47	37	30	31	38	30	36	21	23	13
30	31	32	39	34	28	38	27	31	25	31	37	41	31	35	27	33	32	24	16
27	45	29	37	30	37	28	29	27	27	34	35	30	41	33	33	33	23	25	19
34	30	33	34	36	28	30	31	31	24	30	34	32	30	31	35	35	24	26	30
17	31	39	31	36	38	37	40	24	27	29	31	20	26	38	31	24	38	34	36
27	27	19	29	32	34	37	47	34	29	17	30	38	34	30	26	32	37	28	34
20	22	34	40	29	40	30	37	38	26	24	28	31	32	26	31	29	29	38	39
23	21	26	24	42	31	34	35	40	39	16	19	28	30	28	29	28	38	42	48
29	24	28	23	26	27	28	21	45	**65**	11	18	15	26	24	29	34	46	50	**54**
Singapore										**Taiwan**									

Note: in each sub-table, the ranks for the stock index returns are on the horizontal axis in ascending order while the ranks for the exchange rate returns are on the vertical axis in ascending order. The upper left corner includes observations in the lowest 10th percentile for both returns series and the lower right corner includes observations in the highest 10th percentile for both returns series[12].

Results of the GARCH models

In order to make sure that a series of i.i.d. Uniform (0, 1) observations are fitted to the copula models, we need to correctly specify the marginal models: we model each asset return series using AR(*k*)-GARCH(*p*, *q*) or AR(*k*)-*t*-GARCH(*p*, *q*) type models, whichever is suitable to the specific return series. We experiment with different terms of AR and GARCH until we find the best fit for the data. The parameter estimates and standard errors for the marginal distribution models are reported in Table 4 and Table 5. Only the highly significant (with 5 percent significance level at least) autoregressive terms and GARCH terms are reported in the table. Serial correlation in the raw stock index returns and foreign exchange rate returns can generally be captured with up to an AR(5) term. The exceptions are the Indonesian stock index returns (with a significant AR(10) term) and Indonesian foreign exchange rate returns (with a significant AR(9) term), indicating a long memory in the raw returns series. For most of the return series, GARCH(1,1) is sufficient to model the conditional heteroskedasticity, but some require higher Arch/Garch terms. This is shown by significant Arch2, Arch3, and Garch8 terms for Indonesian foreign exchange rate returns. A Gaussian conditional probability is sufficient for most of the marginal models, except for the stock index returns of South Korea. The estimated degree of freedom is reported in the respective tables for those returns more suitable for t-GARCH models.

Table 4 GARCH Models for Stock Index Returns

Variable	C	AR1	AR5	AR10	Arch1	Garch1	DoF
Stock index							
Indonesia	0.0010	0.1363		0.0419	0.1317	0.8465	
	(0.0003)	(0.0194)		(0.0176)	(0.0090)	(0.0085)	
S. Korea	0.0012				0.0779	0.9205	7.19
	(0.0003)				(0.0099)	(0.0093)	(0.91)
Singapore	0.0004	0.0991	−0.0307		0.1487	0.8270	
	(0.0001)	(0.0151)	(0.0138)		(0.0072)	(0.0073)	
Taiwan	0.0005	0.0500			0.0735	0.9204	
	(0.0003)	(0.019)			(0.0061)	(0.0064)	

Note: numbers in parentheses are standard errors.

We also perform goodness-of-fit tests to test for serial independence of the standardized residuals and the probability integral transforms. We employ the Ljung-Box Q-statistic lack-of-fit hypothesis test which is based on the Q-statistic:

$$Q = N(N+2)\sum_{k=1}^{L} \frac{r_k^2}{(N-k)} \tag{13}$$

where N = sample size, L = number of autocorrelation lags included in the statistic, and r_k^2 is the squared sample autocorrelation at lag k. The Q-statistic is asymptotically Chi-square distributed under the null hypothesis. The *p*-values from the Ljung-Box tests are from 0.08 to 0.98, implying that we cannot reject the null hypothesis that the probability integral transforms are serially independent, and thus the marginal models are not mis-specified. In the next subsection, we discuss the results of the copula models.

Table 5 GARCH Models for Foreign Exchange Rate Returns

Variable	Indonesia	S. Korea	Singapore	Taiwan
C			0.0001	
			(0.00004)	
AR1	−0.0994	0.0415	−0.0480	
	(0.0217)	(0.0199)	(0.0148)	
AR4			0.0402	
			(0.0145)	
AR5				0.0662
				(0.0212)
AR9	0.0405			
	(0.0195)			
Arch1	0.1183	0.1636	0.0779	0.123
	(0.014)	(0.0078)	(0.004)	(0.0069)
Arch2	0.0611			
	(0.0179)			
Arch3	0.0995			
	(0.0181)			
Garch1	0.2221	0.8364	0.9053	0.8162
	(0.1054)	(0.0065)	(0.004)	(0.008)
Garch8	0.499			
	(0.0518)			

Note: numbers in parentheses are standard errors.

Empirical results of the static copula models

Parameter estimates of the SJC copula, Student's t-copula, and Clayton copula models are presented in Table 6. We observe significant lower tail dependence and upper tail dependence for Indonesia, South Korea, and Taiwan. For Singapore, there is no evidence of tail dependence, i.e. the tail dependence parameters are not significant at either tail. Indonesia (λ_l = 0.1318, λ_r = 0.0528) and South Korea (λ_l = 0.1992, λ_r = 0.0501) exhibit asymmetric tail dependence, while Taiwan shows symmetric tail dependence as the estimated parameters are not significantly different, with λ_l = 0.0872 (0.024) and λ_r = 0.0846 (0.022). The estimated degrees of freedom (*v*) of the Student's t-copula range from 6.74 (Korea) to 16.06 (Taiwan), indicating bivariate non-normality between the returns distributions of the two markets for the countries under study. This further confirms that using the linear correlation coefficient as a measure of dependence between financial returns can give misleading results. For Singapore, even though there is not enough evidence to show that there exists extreme co-movement between the equity-currency markets, the estimated degree of freedom parameter of 12.12, shows that, it is not reasonable to assume a bivariate normal distribution in modeling the dependence between the two returns series.

Empirical results of the dynamic copula models

Next we look at the dynamics of the tail dependence measures. Since the static copula results indicate no tail dependence in Singapore's financial markets, we focus on the three emerging markets. We apply Patton's (2006) time-varying SJC copula to examine the conditional bivariate distribution of the returns series for Indonesia, South Korea, and Taiwan. Table 7 reports the parameter estimates along with the static SJC copula results for convenience. Our empirical results show that the autoregressive terms for both tails of the Korea pair (lower tail β = 0.8947, upper tail β = 0.9737), the upper tail of Indonesia pair (β = 0.9210), and the lower tail for Taiwan pair (β = 0.9079), are significant, indicating high persistence in the dependence level. The parameters for the lower tail dependence coefficient of the Indonesia pair are not significantly different from zero, indicating that there is no significant change in the degree of the tail dependence.

Table 6 Estimation of Copula Parameters and Tail Dependence

Pairs	Parameters	SJC copula	t-copula	Clayton copula
Indonesia	V		10.46* (2.32)	
	λ_l	0.1318* (0.022)		0.1345* (0.010)
	λ_r	0.0528* (0.020)		
	Llv	115.34	109.46	96.87
	AIC	**−226.69**	−216.92	−191.74
	BIC	**−214.65**	−210.90	−185.72
South Korea	V		6.74* (0.95)	
	λ_l	0.1992* (0.023)		0.1641* (0.011)
	λ_r	0.0501* (0.022)		
	Llv	156.03	160.09	138.12
	AIC	−308.06	**−318.18**	−274.23
	BIC	−296.00	**−312.15**	−268.20
Singapore	V		12.12* (2.17)	
	λ_l	0.0258 (0.016)		0.0526* (0.008)
	λ_r	0.0000		
	Llv	31.5700	37.5400	28.1200
	AIC	−59.1300	**−73.0700**	−54.2400
	BIC	−45.9300	**−66.4700**	−47.6400
Taiwan	V		16.06* (5.38)	
	λ_l	0.0872* (0.024)		0.1213* (0.011)
	λ_r	0.0846* (0.022)		
	Llv	104.15	105.05	73.62
	AIC	−204.31	**−208.10**	−145.24
	BIC	−192.25	**−202.07**	−139.22

Note: λ_l and λ_r are lower and upper tail dependence parameters; Standard errors are in parentheses; * significant at 5 percent level.

Table 7 SJC copula and time-varying SJC copula results

Country	Parameter	SJC	copula	Time-varying SJC copula	
		λ_U	λ_L	λ_U	λ_L
Indonesia		0.0528**	0.1318**		
		(0.020)	(0.022)		
	ω			0.232	1.2622
				(0.918)	(2.376)
	α			-1.611	-10.000
				(7.010)	(19.563)
	β			0.9210**	0.0667
				(0.335)	(1.806)
	AIC	-226.686		**-247.877**	
	llv	115.343		129.939	
Korea		0.0501**	0.1992**		
		(0.022)	(0.023)		
	ω			0.0719*	0.3709
				(0.039)	(0.266)
	α			-0.5201	-1.8048
				(0.350)	(1.390)
	β			0.9737**	0.8947**
				(0.026)	(0.098)
	AIC	-308.062		**-366.918**	
	llv	156.031		189.459	
Taiwan		0.0846**	0.0872**		
		(0.022)	(0.024)		
	ω			0.7174	0.1261
				(0.677)	(0.173)
	α			-10.000**	-1.1337
				(0.001)	(0.680)
	β			0.0051	0.9079**
				(0.361)	(0.045)
	AIC	-204.3076		**-208.866**	
	llv	104.154		110.433	

Note: α and β are parameters controlling the dynamics of the lower and upper tail dependence in eq (10); Numbers in parentheses are standard errors.

To illustrate the evolving time path of the degree of tail dependence coefficients, in Figure 1, Figure 2, and Figure 3 we plot the conditional upper and lower tail dependence implied by the time-varying SJC copula model. In the figures, we also plot the time-varying difference between the lower tail and upper tail coefficients, as calculated by $\lambda_l - \lambda_r$. Under symmetry, this difference should be zero. From the bottom plot of Figures 1 and 2 we note that conditional lower tail dependence is greater than conditional upper tail dependence almost all of the time for the Indonesia pair and the South Korea pair, supporting our conclusion of asymmetry in tail dependencies for these two pairs. In the case of Taiwan

(Figure 3), the difference between the lower tail coefficient and upper tail coefficient fluctuates around zero, indicating that the lower and upper tail parameter values are not significantly different, as we have concluded earlier based on unconditional copula results.

Figure 1 Time path of conditional tail dependence coefficients: Indonesia

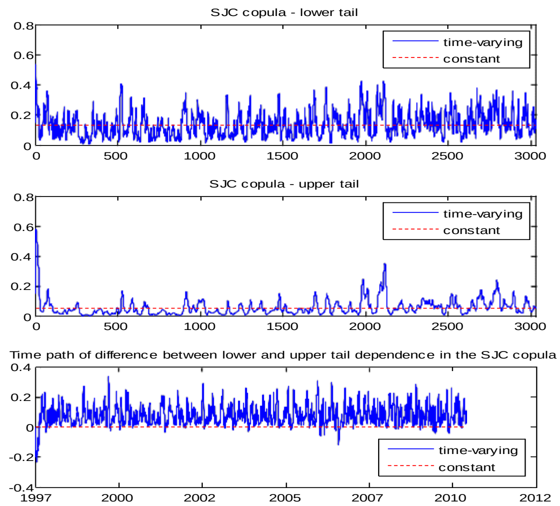


Figure 2 Time path of conditional tail dependence coefficients: South Korea

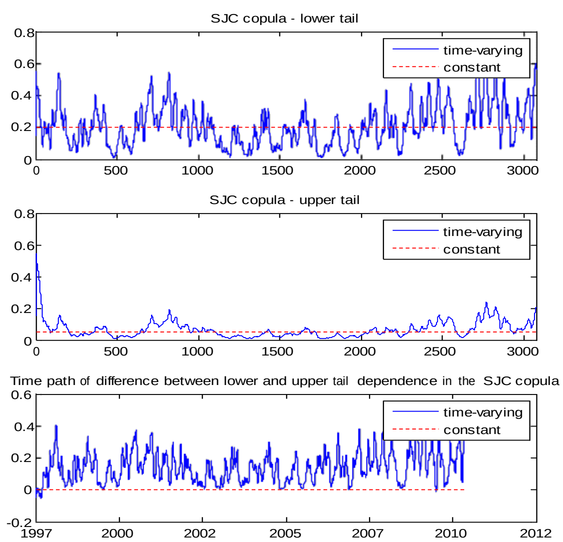
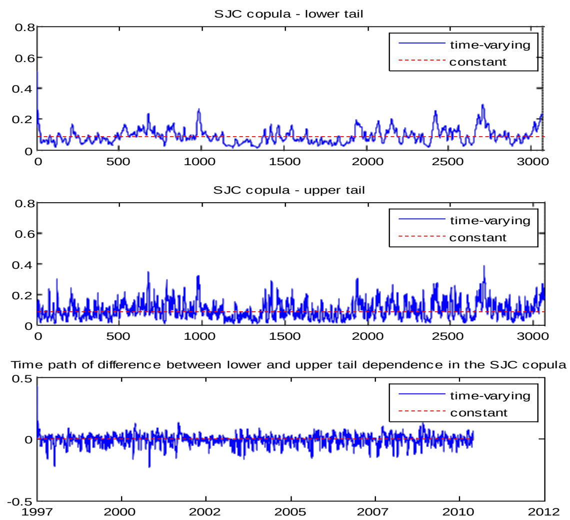


Figure 3 Time path of conditional tail dependence coefficients: Taiwan



We can compare the relative performance of the competing copula models using Akaike's information criterion (AIC). For the three pairs, we find a reduction of the AIC in the time-varying SJC model (the Korea pair decreased the most and the Taiwan pair decreased the least), indicating the dynamic copula model performs better than its static counterpart.

CONCLUSION

In this paper, we examine the degree of dependence at the extremes of the bivariate distribution between the stock index returns and foreign exchange fluctuations in four East Asian countries via copula methods. First we apply AR-GARCH or AR-t-GARCH type models to filter the raw returns data to ensure our copula inputs are serially independent, then we fit different copula models to detect any tail dependence behavior between the stock index returns and foreign exchange rate returns for the selected countries. Using static copula models, our major findings are the following. For the more advanced economy, Singapore, there is no evidence of tail dependence between the two returns series. Indonesia and South Korea have significantly higher lower tail dependency than upper tail dependency, thus asymmetric tail dependencies. For Taiwan, the tail dependence is significant and similar between the lower and upper tails, suggesting symmetric tail dependence behavior.

We also employ Patton's (2006) conditional SJC copula model to examine the dynamics of tail dependence coefficients between stock index returns and foreign exchange rate returns for the three emerging markets. The empirical results show that the autoregressive terms for both tails of the South Korean pair, the upper tail of the Indonesian pair, and the lower tail for the Taiwanese pair are significant, indicating high persistence in the dependence level. Using graphical analysis, the conditional lower tail dependence is greater than the conditional upper tail dependence almost all the time for the Indonesian pair and the South Korean pair, supporting the conclusion of asymmetry in tail dependencies for these two countries.

Our empirical findings have important finance implications in risk management and asset pricing. For investors seeking to diversify their portfolio into emerging financial markets, ignoring the joint downside risk would underestimate the value-at-risk (VaR), which is a common risk measure in risk management. Tail dependence serves as a true measure for systematic risk in times of financial crisis and global investors should be compensated for exposure to such risk during joint market downturns. These results can provide important guidance for investors who consider international diversification into this economic region. International investors, seeking diversification into Indonesia and South Korea stock markets, will more likely experience extreme double losses (one in the stock market and the other in the currency market when translating into home currency returns) than extreme double gains. Therefore hedging equity investments with currency derivatives is highly recommended. For investments made in the advanced market, currency hedging does not seem necessary.

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ENDNOTES

1. "Stock oriented" models view exchange rates as equating the supply and demand for assets such as stocks and bonds (e.g. Branson (1983) and Frenkel (1983)).

2. "Flow oriented" models focus on the current account or the trade balance. Changes in exchange rates affect international competitiveness and trade balances, thereby influencing real income and output (e.g. Dornbusch and Fisher (1980)).

3. Currency risk is a form of risk that arises from the change in price of one currency against another and it is a key element in foreign investment. International investors face currency risk if their positions are not hedged.

4. Copulas, derived from the Latin work *copulare*, meaning to connect or to join, were first introduced by Sklar (1959) to study probabilistic metric spaces. In statistics, a copula is a function linking marginal variables into a multivariate distribution. The copula method has become a very popular tool to model financial risk factors in the past decade.

5. As stated in Patton (2006, pp.533), Sklar's Theorem implies that we may link any two univariate distributions, which are not necessarily from the same family, with any copula, to define a valid bivariate distribution. With a corollary to Sklar's theorem, as given in Nelson (1999) for example, we are able to extract the copula from any given multivariate distributions and use it independently of the marginal distributions of the original distribution. For example, we are able to extract the normal copula from a standard bivariate normal distribution.

6. Tail dependence allows investors to measure the probability of simultaneous large losses or gains. It is extremely important for safety-first investors since the lower tail dependence between stock returns and exchange rate fluctuations measures the likelihood of a large loss in foreign investment.

7. Joe and Xu (1996) compared the efficiency of the IFM estimator with the ML estimator via simulation

and find that the ratio of the mean square errors of the IFM estimator to the ML estimator is close to 1, indicating the high efficiency of the IFM estimator.

8. The dynamic copula, or conditional copula, has the properties of an unconditional copula. See Patton (2006) for more details.

9. Most of the broadly-used market indexes today are capitalization-weighted indexes, such as S&P 500 and Nasdaq. Large companies have large shareholder bases, and therefore should have higher relevancy in the index.

10. Since the four countries have their own business days, the observations varied in each country. Indonesia had 3034 observations, Korea had 3074 observations, Taiwan had 3155 observations, and Singapore had 3066 observations.

11. For the same period, S&P 500 had an average daily return of 0.005 and a standard deviation of 1.3651.

12. Table 3 is a contingency table. Let x be the stock index returns series and y be the foreign exchange rate returns series and we rearrange these two series in ascending order to obtain x' and y', so that $x'(t) < x'(s)$ and $y'(t) < y'(s)$ for $t < s$. Then we divide each series evenly into 10 parts and we have a 10 by 10 table. If x and y are perfectly positively correlated, most observations should lie on the main diagonal; if x and y are independent, the number of observations in each cell should be approximately the same; if x and y are perfectly negatively correlated, most observations should lie on the diagonal from the lower-left corner to the upper-right corner. In each sub table of Table 3, the first column represents the bottom 10 percent of the stock index returns, and the last column represents top 10 percent of the stock index returns (the time series is sorted in ascending order (from lowest return to highest return) and divided into ten equal parts). Likewise, the first row represents the bottom 10 percent of the exchange rate returns and the last row represents the top 10 percent of the exchange rate returns (the time series is sorted in ascending order (from lowest return to highest return) and divided into ten equal parts). Therefore, the number in the upper-left corner (97 for S. Korea) represents the number of trading days when both the stock index return and foreign exchange rate return were below their respective 10th percentile. Similarly, the number in lower-right corner (81 for S. Korea) indicates the number of trading days when both the stock market and the currency market had a return above their respective 90th percentile.

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Economic Dimensions of the Foreclosure Crisis: A Focus on the New York City MSA

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Eric Doviak**

ABSTRACT

Employing Home Mortgage Disclosure Act data on loan originations from 2004 – 2010 and 2010 New York State pre-foreclosure filing notices, this study seeks to identify the correlation between some characteristics of census tracts and the distribution of pre-foreclosure filing notices and high cost loans within the New York City metropolitan area from 2006 through 2012. The findings are examined within the context of the census tracts within which borrowers resided. American Community Survey data on employment-population ratios, poverty rates, and median household income were then matched to our HMDA-PFF dataset to obtain a measure of the relationship of particular census tract variables to default rates. Our analysis of the data finds that differences in census tract characteristics have a statistically significant effect on default and foreclosure patterns.

1 INTRODUCTION

This study examines mortgage default rates across census tracts within the New York City metropolitan area from 2006 through 2012. Our investigation begins with the question of the extent to which community characteristics - employment to population ratios, poverty rates, the ratio of loan amounts to median home values by census tract, and median household income explain variances in default and foreclosure rates across the New York City metropolitan area's census tracts.

In an earlier study, "Who Defaults on their Home Mortgage?" (Doviak and MacDonald, 2012), the authors examined the significance of loan characteristics, including measures of loan amount, interest rate paid, loan type, and high cost vs. non-high cost loan, as well as borrower characteristics, including income, race, ethnicity, and the presence of a co-borrower on the probability of loan default. This study found a strong correlation between the receipt of a high-cost loan and/or a pre-foreclosure filing notice and the loan amount, borrower race and ethnicity, and borrower income.

A pre-foreclosure filing notice (PFF) is a formal notification that mortgage servicers are required to send to delinquent borrowers at least 90 days prior to filing for foreclosure on a primary residence in the State of New York. Under the law (enacted on December 15, 2009), servicers must inform homeowners that their loan is in default, indicate the amount necessary to cure the default and indicate measures that can be taken to avoid foreclosure, such as negotiating a loan modification with their lender and/or consulting with a non-profit housing counselor (New York State Division of Financial Services, 2009).

In an effort to identify loan and borrower demographic characteristics that may make a borrower more likely to default, we matched 2004 – 2008 loan origination data from the Home Mortgage Disclosure Act (HMDA) to 2010 pre-foreclosure filing (PFF) data from the New York State Department of Financial Services (DFS) and traced loans from origination to default.[1]

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Three key findings emerged from this study. One was that a strong predictor of default is the amount borrowed. This finding would not be surprising. Everything else equal, a borrower who took out a larger loan was left with less equity in the home (and often negative equity) after home prices tumbled during the recent economic and financial crisis.

Second, borrowers with incomes between $80,000 and $200,000 appeared to have received disproportionately more pre-foreclosure filing notices than borrowers in lower and higher income ranges. Black and Latino borrowers were disproportionately represented within this income range, suggesting another reason the foreclosure crisis had a greater impact on these borrowers.

Finally, the interest cost of the loan was found to be a strong predictor of default. Borrowers who obtained "high-cost" loans were more likely to receive a pre-foreclosure filing, and lower-income borrowers were more likely to have received a high-cost loan than borrowers with higher incomes.

While the study could not conclusively prove discriminatory lending practices, it did find that Black and Latino borrowers were more likely to have received a high cost loan, since the HMDA data captures the difference in the rate spread between loans originated to minorities and loans originated to whites.

However, the inability to prove discrimination stems from the limitations of the HMDA data itself. There is simply no basis upon which to conclude that borrowers paying higher interest rates were doing so because they were deemed by the lender to be "higher risk." The HMDA data, lacking measures of borrower credit scores and loan-to-value, simply makes drawing such a conclusion difficult.

2 SUMMARY OF STUDY

The present study seeks to expand upon this initial inquiry by examining information about the characteristics of the communities within which borrowers reside through the inclusion of American Community Survey data. Were high cost loans and higher default rates correlated with census tracts characterized by particular criteria? Did communities characterized by higher poverty rates, lower employment rates, and lower ratios of applicant income to median household income experience higher rates of default and a greater prevalence of high cost loans? How significant was loan amount to median home values in these same communities?

This study, therefore, continues the examination of variables that have contributed to default rates by employing the same matched PFF-HMDA data set together with American Community Survey census tract level data to study the influence of community factors on loan defaults and the percentage of high cost loans.

The review of the literature that follows briefly examines studies that have examined some of the characteristics of default and foreclosure patterns based upon the characteristics of the communities in which loans were originated. Some of these studies employ either Census tract or MSA level data in conjunction with HMDA data to obtain measures of the racial/ethnic composition of metropolitan areas to examine which communities had the highest concentration of high cost loans. Others examine differences in mortgage interest rates by race and ethnicity by census tract using either the Census Bureau's American Housing Survey or American Community Survey data. Studies that have been able to access a proprietary data set of actual loans have been able to make the connection between loan and borrower characteristics more convincingly, and have been able to point to some evidence of different lending practices based on race and ethnicity. Overall, however, studies lacking borrower data are confronted with the limitations inherent within the HMDA data, which lacks critical borrower information such as credit scores and loan-to-value measures, making a generalization applicable across neighborhoods difficult.

Thus in terms of our research, there would be a two-step process in documenting evidence of discriminatory lending. First is the necessity of identifying the correlation between some characteristics of census tracts and the distribution of pre-foreclosure notices and high cost loans. Second would be a more formal analysis that examines the probability of default within predominantly minority and non-minority census tracts, measured as a function of both census tract characteristics and borrower characteristics.

The focus of the current investigation, however, is limited to ***the first of these goals*** - to identify variables that could provide a more robust measure of the correlation between community characteristics, high cost loans and default rates. Abundant data document the increased reliance on debt financed household spending merely to 'keep up' with the rising cost of living. This trend is a strong indicator of rising income inequality. Thus measures of household income, poverty rates, employment to population ratios, and measures of loan to value are key in this inquiry. Did differences in median household income, poverty rates and employment levels within census tracts contribute to different outcomes in terms of the likelihood of default (as measured by the receipt of pre-foreclosure filing notices) or receipt of a high cost loan?

The data employed for this study include 2010 New York State pre-foreclosure (PFF) filings, Home Mortgage Disclosure Act data for loan originations from 2004 through 2008, and American Community Survey data from the U.S. Census Bureau. The detail obtained from the matched PFF-HMDA originations data has enabled an analysis of the characteristics of borrowers who were more likely to default, a comparison of loans that entered the foreclosure process to those that did not, and a comparison of defaulted loans across years in which they were originated. The American Community Survey (ACS) data facilitate development of a more comprehensive picture of the characteristics of the communities in which borrowers reside through the inclusion of data on poverty and employment rates, the ratio of applicant income to median household income, and the ratio of loan amount to median census tract home value, which serves as a proxy for a measure of loan to value.

The paper's methodology begins with the matched pre-foreclosure-HMDA originations dataset for the five boroughs of New York City and then identifies the census tract of each property in the PFF dataset. These data are then compared to a database of census tract coordinates available from the Census Bureau. Thus, with demographic information on borrowers from HMDA and loan characteristic data from the pre-foreclosure filings, the ACS data make it possible to extract aggregate demographic data at the census tract level to obtain measures of default rates and high cost loans based upon census tract characteristics.

We then conclude with a summary of the principal findings of our analysis. In brief, we find that the share of both high-cost loans and pre-foreclosure filing notices tended to be greater in census tracts characterized by higher poverty rates, lower employment-population ratios, and higher loan-to-value ratios.

3 REVIEW OF THE LITERATURE

A number of recent studies have looked at HMDA data in the context of the communities within which borrowers reside to discern lending patterns in minority communities. In many such studies, it is not difficult to demonstrate that high-cost lending was most prevalent in predominantly minority communities, but it has always been difficult to take these analyses a step further to show conclusive evidence of discriminatory lending practices because of the lack of key variables – principally credit scores and loan-to-value data - in the HMDA data. In cases where studies have had access to proprietary or other loan datasets, there has been more of a foundation on which to link loan type to race (Bocian et al.,2006; Gerardi and Willen, 2008).

However, when employing just the HMDA data to study the broader market, researchers are generally confined to finding correlations between community characteristics such as race, ethnicity, and similar demographics and the probability of receiving a high-cost loan. This is still the case with studies that examine trends at the MSA level.

Rugh and Massey (2010) for instance attempt to link the correlation between high-cost lending and the patterns of residential segregation to the subprime foreclosure crisis. To find the link, they obtain the total number of foreclosures between 2006 and 2008 from RealtyTrac's foreclosure database and compute the foreclosure rate as the number of filings per household unit. They then use the 2004-2006 HMDA data to compute the share of high-cost loans[2] in each MSA. To derive a measure of regulatory oversight, they also compute the share of loans within the MSAs that were originated by institutions covered under the Community Reinvestment Act (CRA). Employing an OLS multiple regression model, the authors regress the number and rate of foreclosures in the nation's 100 largest MSAs on two measures of segregation: residential unevenness and spatial isolation. Their results suggest that residential segregation and the share of high-cost loans are both positively correlated with the number and rate of foreclosures across U.S. metropolitan areas.

One omission in their published paper however is a regression of the high-cost lending share on measures of racial and ethnic segregation. If segregation enabled lenders to target minorities for high-cost loans (as Rugh and Massey claim) then the next step should have been to regress the high-cost lending share on measures of segregation. If the coefficient were positive and statistically significant, then their claim of racial and ethnic targeting would have a firmer foundation.

Other studies have employed either census tract or MSA level data in conjunction with the HMDA data to obtain measures of the racial/ethnic composition of metropolitan areas to examine which communities had the highest concentration of high cost loans (Squires et al., 2009). Following is an overview of studies that have examined HMDA data in the context of where borrowers reside to discern patterns of lending in minority communities. Some of these studies examine data at the MSA level, while others examine census tract level data in investigating lending patterns.

Squires et al. (2009) use the 2000 Census data to construct a dissimilarity index to obtain a measure of the ten most segregated and the ten least segregated metropolitan areas in the U.S. They then compare the indices derived to the percentage of high-cost loans originated. Using 2006 HMDA data and the 2006 American Community Survey, they employ a multivariate OLS model (to control for several MSA-level variables) and find that racial segregation is a significant predictor of the percentage of high-cost loan originations in an MSA. Their results suggest that a 10 percent increase in black segregation was associated with a 1.4 percent increase in high-cost loans.

In another study using 2001 American Housing Survey data, Susin (2003) examines differentials in mortgage interest rates by race and ethnicity at the census tract level. Employing a sample of homeowners with mortgages, Susin examines interest rates in relation to a number of both loan and borrower characteristics in the context of the census tracts in which they reside. His study considers the race/ethnicity of the borrower, home value and loan characteristics as well as neighborhood characteristics, including poverty rates and the percentage of Black and Latino residents in the census tracts in which the borrowers reside. His study finds that African American borrowers paid an average of 44 basis points more than white borrowers on their loans.

In an extensive 2006 study, Boehm and Schlottmann examine a pooled sample of MSA specific American Housing Survey data. Specifically, they select a large sample consisting of 5,000 households for each of 41 MSA's from 1998 through 2004, resulting in a rather large sample of 200,000 observations. The authors look at both conventional and FHA/VA mortgages to identify differences in mortgage interest payments made by Black, Latino and white borrowers of first lien mortgages. They find that across the full sample, Black borrowers paid higher interest rates on first mortgages in both the conventional and FHA/VA markets. Both non-white and white Latino borrowers paid significantly more in the conventional loan market than their white counterparts at 14.6 and 9.2 basis points, respectively. Blacks paid an additional 30.6 basis points.

Others have also found a link between the racial composition of a neighborhood and the share of subprime lending in that neighborhood at the MSA level. In a joint study conducted by several community organizations, Bromley et al. (2008) focused on subprime lending activity in 2006 across seven large metropolitan areas in the U.S. Data collected on the number of high-risk loans originated by a sample of 35 subprime lenders during that year indicated that these lenders accounted for an estimated 20 percent of the market share of subprime loans in predominantly minority neighborhoods within these metropolitan areas. Further, more than 40 percent of the loans made by high-risk lenders in these metropolitan areas were in neighborhoods where the share of minority residents was 80 percent or more. Subprime lenders' market share was also positively correlated with the percentage of minority residents within a given census tract.

While these and similar studies clearly demonstrate that Black and Latino borrowers obtained a disproportionately greater share of high-cost and subprime loans, the evidence that this trend reflects discrimination suffers from the limitations inherent within the HMDA data. The lack of information on credit scores in the HMDA data may explain some of the disparities in the rate spreads among individual borrowers, but it is difficult to see how this could be applicable across neighborhoods. In other words, it is certainly possible to imagine individual cases where a high-income black borrower's credit score is lower than a low-income white borrower's credit score; at the same time, however, it is difficult to see how the average credit score of borrowers in a high-income black neighborhood could be lower than the average credit score of borrowers in a low-income white neighborhood.

With the exception of Susin (2003), these studies have focused their analyses mostly at the MSA level in their examination of the relationship between the race and ethnicity of borrowers and the disproportionately greater share of high cost and/or subprime loans. While they have, at the same time, contributed extensively to the literature on the evidence of discriminatory lending practices, the focus at the MSA level and or the characteristics of MSAs poses limitations in getting at the widely varying characteristics of communities within those MSAs.

The present study seeks to expand upon the scope of these inquiries into high cost lending to focus on census tract level data that include several additional characteristics of the communities that are believed to have played a role in the percentage of high cost loans and the incidence of default. Studying census tract data for the New York MSA, this analysis examines the influence on the percentage of high cost loans of poverty rates, employment to population ratios, the ratio of loan amount to median home value, and the ratio of applicant income to median household income. The study then examines the relationship between the percentage of high cost loans and rates of default across each of these variables by employing census tract data in conjunction with HMDA-PFF data. Using such a framework, this census tract level study offers the opportunity to move beyond some of the limitations posed by use of the HMDA data alone in the study of community characteristics by including data on default rates at the census tract level. The information such a study yields can then provide the foundation for future examinations of lending practices.

4 DATA

Three datasets are employed for this analysis – the New York State Pre-foreclosure filing data for 2010, Home Mortgage Disclosure Act data for 2004 through 2008, and American Community Survey Data from the U.S. Census Bureau. The Pre-foreclosure filing data from the New York State Division of Financial Services became available in 2010 with the passage of legislation requiring lenders and loan servicers to provide delinquent borrowers with 90-day advance notice that their loans were in default to give these borrowers time to work with loan counselors to reach a modification agreement before formal foreclosure proceedings began.

Thus, since February 13, 2010, mortgage servicers have been required to file the notices with the New York State Division of Financial Services (formerly the NYS Banking Department), which has collected an extraordinary level of detail on the loans. Among the many data fields collected are: the property address, the names of the borrowers, the current monthly payment, the delinquent contractual payments, the interest rate, whether the loan is a fixed-rate or adjustable-rate mortgage, the date and the amount of the original loan, the lien type, the loan term, whether the loan has been modified and whether an investor's approval is necessary to modify the loan. If the loan progresses to a *lis pendens* filing (i.e. the first step in the foreclosure process or the filing of the complaint) then servicers are also required to follow up on their initial filing with information on the entity filing for foreclosure.

The detail captured in the PFF data makes three forms of analysis possible. First, the defaulted loans can be matched to publicly available data on originations from the Home Mortgage Disclosure Act (HMDA). By combining the HMDA and PFF data, it is possible to see which borrowers were more likely to default. Second, it is possible to compare the loans that entered the foreclosure process to those that did not, and finally, the "Full PFF" dataset can be used to compare defaulted loans across the years in which they were originated.

The first two datasets – which compare originations to defaults and compare defaults to *lis pendens* filings – effectively generate a quasi-longitudinal analysis, which makes it possible to track the universe of New York State home mortgages from origination to default to foreclosure. We use the term "quasi-longitudinal" however, because the PFF data only provide information on borrowers who defaulted in 2010. Data on the borrowers who did not default or defaulted in subsequent years are not available. While there is no way to perfectly match the PFF data to the HMDA data, the matching strategy employed generates a reasonably accurate result, although we cannot be certain of full verification of all matches.

These combined data have facilitated the identification of borrower characteristics and loan level characteristics that are more likely to be correlated with default. Principal among some of the findings of an earlier study, was that Black and Latino borrowers were more likely than other borrowers to have received high-cost loans, pre-foreclosure filing notices and to have obtained relatively larger loans than the population overall (Doviak and MacDonald, 2012). While the evidence discussed in our earlier study pointed to the possibility of discriminatory lending practices, and several related studies bore out similar findings, the lack of critical data either from HMDA or PFF on loan to value and credit scores made it difficult to definitively “prove” such a finding.

With the incorporation into the present study of a third data set from the American Community Survey, it is our goal to obtain a more comprehensive picture of the relationship of default rates to the communities within which borrowers reside. Thus, the ability to include data on poverty rates, employment-to-population ratios, the ratio of applicant income to median household income, and the ratio of loan amount to median home value at the census tract level effectively adds the kind of information about borrowers and their communities that may provide more comprehensive information about the correlation between the receipt of a pre-foreclosure filing notice, the receipt of high-cost loans and community demographics.

5 METHODOLOGY

The starting point here is the pairing of a HMDA dataset on loan originations from 2004 – 2008 with pre-foreclosure filing notices issued in 2010 to borrowers within the five boroughs of New York City. The study examines first-lien mortgages to ensure comparability across loans. The resulting 130,912 first-lien mortgages that were originated in the years 2004-2008 account for 70 percent of all PFF filings on first-lien mortgages. The years 2004-2008 were selected to enable a comparison of the PFF data to the data on originations from the Home Mortgage Disclosure Act (HMDA). We chose 2004 as the first year, because the variables in the pre-2004 HMDA data were much less extensive.

The HMDA originations data contain the FIPS (Federal Information Processing Standards) county code and census tract number of each property. The FIPS code is a five-digit code assigned to each county, the first two digits representing the state and the last three digits, the specific county within the state. This is particularly valuable because census tracts have a small population (typically between 2,500 and 8,000 people) which is fairly homogeneous in terms of socio-economic characteristics and living conditions (U.S. Census Bureau, 2000).

The first step in matching the PFF data to the HMDA data is to use the address information to identify the census tract of each property in the PFF dataset. To identify the census tracts, Erle’s (2005) “Geo-Coder-US-1.00” Perl module is used in conjunction with the U.S. Census Bureau’s (2007) TIGER/Line Files. After using this module to create a database of New York State addresses from the TIGER/Line Files, the database was queried to obtain the latitudes and longitudes of the property addresses in the PFF dataset. Once the coordinates were generated, these were compared to a database of census tract coordinates that was generated from the U.S. Census Bureau’s (2005) “Cartographic Boundary Files.”

The HMDA data provide demographic data on borrowers such as race, ethnicity, and income, as well as information on loan originators. The 2010 New York State pre-foreclosure filings data provide information on loan type, loan amount, length of delinquency and other loan characteristics. The matching of these two datasets provides us with the characteristics of borrowers who defaulted on their loans. It also provides us with information on the type of loan where default was more likely to occur.

Next, data from the U.S. Census American Community Survey are introduced to extract aggregate demographic data at the census tract level to obtain measures of default rates based upon census tract characteristics, as well as a measure of the tract-level variables that are most significantly linked to default. Supplementing the HMDA-PFF dataset with ACS data provides a rough measure of loan-to-value and provides a clearer picture of the relationship between poverty rates, employment and labor market conditions and the foreclosure crisis at the community level.

Census tracts within the five boroughs of New York City are the focus of this study of the relationship between borrower and loan level characteristics and of the economic characteristics of the census tract within which the loan was originated. Thus, several census tract level variables are employed to determine the extent to which these are correlated with borrower default rates.

We begin with variables that can provide some measure of the relationship between income, employment levels and poverty rates and the probability of receiving a pre-foreclosure filing notice at the census tract level. Specifically, we examine borrower income relative to median household income, the employment to population ratio for the population over 16 years, poverty rates, and borrower loan data relative to median home values at the tract level. Through this process, we seek to obtain a picture of the characteristics of borrower income, loan amount, receipt of a pre-foreclosure filing and loan type, relative to the characteristics of the census tract within which the mortgage was originated.

The pairing of total number of pre-foreclosure filings (PFFs) to HMDA originations at the census tract level will make possible an analysis of default rates which can then be correlated directly with census tract characteristics. With this information, it is the goal of this study to be able to obtain a clearer picture of the correlation between the characteristics of communities at the census tract level, loan type and rates of default.

6 ANALYSIS, FINDINGS, SUMMARY TABLES

The study finds that the distribution of high-cost loans and default rates (as measured by receipt of a pre-foreclosure filing notice) tended to be greater in census tracts characterized by higher poverty rates, lower employment-population ratios, and higher loan-to-value ratios. This trend is revealed in the new data set combining aggregate census tract data with the HMDA-PFF data.

This combined HMDA-PFF-ACS data indicate that census tract poverty rates are significantly correlated with the receipt of a high-cost loan. As illustrated in Table 1, where census tract poverty rates range from below 2.0 percent to less than 4.0 percent, the lowest percentage of high cost loans was originated. As the percentage of population below the poverty level income rises, the percentage of high-cost loans increases substantially.

Table 1: Percentage of Families Below Poverty Income Level by Receipt of a High Cost Loan

Percentage of population Below poverty income in tract	High-cost	Non high-cost	Total loans	Percent high-cost
Under 2.0%	44,660	305,077	349,737	12.8%
2.0 to 3.9%	41,470	228,513	269,983	15.4%
4.0 to 7.9%	65,395	288,586	353,981	18.5%
8.0 to 11.9%	41,204	146,060	187,262	22.0%
12.0 to 15.9%	23,659	80,097	103,756	22.8%
16.0 to 19.9%	15,684	45,938	61,622	25.5%
20.0% and over	34,026	82,453	116,479	29.2%
Totals	266,098	1,176,724	1,442,822	

Source: Combined HMDA-PFF-ACS

The absolute number of high-cost loans is greatest at poverty rates between 4.0 and 7.9 percent; however, even as the number of such loans declines as the percentage in poverty rises, the percent that are high-cost continues to increase. An interesting observation here is that as the share of population below poverty within census tract reaches 20 percent and above, both the number and percentage of high cost loans increase significantly.

Interestingly, however, the percentage of pre-foreclosure filings (notices of default) by percentage of families with census tract income below poverty level seems to reveal an opposite trend (as reflected in Table 2). The percentage of PFFs received is greatest where the percentage of families below poverty level is less than 2.0 percent and between 4.0 and 7.9 percent. In fact, the 4.0 to 7.9 percent range accounts for nearly a quarter of all PFFs, while at poverty rates of 7.9 percent and below, the percentage of PFFs accounts for nearly two-thirds of all such notices, suggesting that the PFF percent declines as poverty rate within the census tract rises.

Table 2. Percent of Families Below Poverty Income by Receipt of a Pre-Foreclosure Filing Notice

Percentage below poverty in tract	Non-PFF	PFF	Total loans	PFF percent	Ratio high cost loans to defaults
Under 2.0	327,169	23,552	350,721	20.7%	1.90
2.0 to 3.9	250,032	19,456	269,488	17.1%	2.13
4.0 to 7.9	327,169	27,762	354,931	24.4%	2.36
8.0 to 11.9	171,564	15,588	187,152	13.7%	2.64
12.0 to 15.9	94,427	9,216	103,643	8.1%	2.56
16.0 to 19.9	55,858	5,689	61,547	5.0%	2.75
20.0 and over	103,736	12,402	116,138	10.9%	2.74
Total	1,329,955	113,665	1,443,620		

Data: Combined HMDA-PFF-ACS

Such findings may seem counter intuitive. However, if we consider the likelihood that fewer loan originations would be made in census tracts characterized by very high poverty rates, the finding appears less surprising. One interesting finding here is that despite this trend, the ratio of high cost loans to defaults clearly rises as the share of families with incomes below poverty within census tract rises, suggesting that among those who did receive high cost loans, the default rate was significantly higher on those loans in census tracts characterized by higher rates of poverty.

The data also reveal that community employment rates are highly significant in relation to the likelihood of receiving a high-cost loan and/or a pre-foreclosure filing notice. High-cost loans appear to be much more likely in census tracts characterized by lower employment/population ratios, likely reflecting a greater instability of employment (Table 3a). Where the employment/population ratio is 55 percent or less of the tract population over the age of 16, the percent of high cost loans is greatest and accounts for more than 44 percent of such loans. One possible explanation is that in tracts where there was a greater concentration of residents with less employment and income stability, there was a disproportionately higher percentage of high cost loans to compensate for the increased risk.

Table 3a: Employment to Population Ratio by Receipt of a High-Cost Loan

Employment/Population (pop over age 16)	Number non high-cost loans	High-Cost loans	Total loans	Percent high cost
Under 50.0%	70.603.5	21,553.9	92,157.4	23.4%
50.0 to 54.9%	125,909.6	32,996.2	158,905.7	20.8%
55.0 to 59.9%	274,176.9	65,194.0	339,370.9	19.2%
60.0 to 64.9%	375,375.3	84,353.1	459,728.3	18.3%
65.0 to 69.9%	242,405.4	50,558.6	292,964.0	17.3%
70.0% and over	88,254.4	11,442.2	99,696.6	11.5%

Source: Combined HMDA-PFF-ACS

The percentage of pre-foreclosure filing notices follows a similar pattern, although it appears somewhat less pronounced in the data (Table 3b). The share of both high cost loans and pre-foreclosure filing notices is noticeably higher where the employment/population ratio is less than 55.0 percent. In the middle of the employment/population distribution – at ratios from 55.0 percent to 66.9 percent – there is little difference in the percent of high-cost vs. non-high cost loans received or in the percent of pre-foreclosure filings. As would be expected at high rates of employment relative to population - 70.0 percent or higher – the incidence of both high cost loans and pre-foreclosure filings are lowest.

Clearly, a high employment/population ratio suggests a comparatively more stable community, one in which employment stability is most likely established and where the probability of job loss is significantly lower. It is also more likely that job loss in such communities would be temporary and re-employment easier, reducing the probability of entering into default and the pre-foreclosure process. Further, residents in tracts characterized by higher rates of employment may have been comparatively less affected by the job losses associated with the financial crisis and thus, had a greater ability to continue making mortgage payments, resulting in a lower proportion of PFFs.

Table 3b: Employment to Population Ratio by Receipt of a Pre-Foreclosure Filing Notice

Employment/Population (pop over age 16)	Number no PFF	Number PFF	Total loans	Percent PFF	Ratio high-cost loans to defaults
Under 50.0%	83,787.2	8,078.3	91,865.5	8.8%	2.66
50.0 to 54.9%	144,965.2	13,653.5	158,618.7	8.6%	2.41
55.0 to 59.9%	312,539.7	26,956.6	339,505.3	7.9%	2.42
60.0 to 64.9%	424,256	36,409.3	460,665.2	7.9%	2.32
65.0 to 69.9%	271,311.0	22,300.7	293,611.7	7.6%	2.27
70.0% and over	93,069.9	6,257.8	99,354.8	6.3%	1.82

Data: Combined HMDA-PFF-ACS

Also consistent with the finding of higher percentages of both high cost loans and pre-foreclosure filings at lower employment to population ratios is the observation that the ratio of high-cost loans to defaults is also higher. Although the absolute number of high cost loans and defaults at rates of employment below 50 percent are comparatively lower than at higher employment to population ratios, the likelihood of receiving a high cost loan and then defaulting is significantly greater.

As discussed in both the literature review and in our own earlier study, one of the shortcomings of drawing a strong conclusion regarding loan characteristics relative to home value is the lack of key loan-to-value data in HMDA. The employment of the combined HMDA-PFF-ACS dataset here, however, allows for the possibility of addressing this issue by obtaining a ratio of borrower loan amounts relative to the median home value by census tract.

Analysis of pre-foreclosure filings in relation to the ratio of loan amount to median home value in census tract (Table 4) clearly indicates that as this tract loan-to-value indicator rises, the percentage of PFFs does as well. Clearly, there is a correlation indicating that the greater the amount of the home purchase financed, the greater the incidence of default. Nearly a quarter or all loans were financed at rates of 90 percent and greater, and accounted for 21.8 percent of total defaults. Such a finding isn't surprising since a greater loan burden poses a considerably higher risk of default in a declining housing market.

Table 4. Receipt of a Pre-foreclosure Filing by Ratio of Loan Amount to Median Home Value in Tract

Ratio of loan amount to median home value in tract	**Number no PFF**	**Number PFF**	**Total loans**	**Percent PFF**	**Ratio – high cost loans to defaults**
Under 50.0%	363,078.0	17,863.3	380,941.3	4.7%	2.74
50.0% to 69.0%	339,138.8	25,372.7	364,511.5	7.0%	2.35
70.0% to 89.0%	319,189.4	33,337.2	352,526.7	9.5%	2.24
90.0% to 99.0%	101,076.7	12,970.8	114,047.5	11.4%	2.24
100.0% or greater	208,803.1	24,234.9	233,038.0	10.4%	2.21

Source: Combined HMDA-PFF-ACS

The relationship between tract loan-to-value and high-cost loans (Table 5) indicates that the percentage of high cost loans increases significantly as loan-to-value increases. Close to 50 percent of high cost loans were originated where tract loan-to-value was 90 percent or more. Interestingly, while just 30 percent of all high cost loans were at loan-to-values of 90 percent or more, the data indicated the significantly greater concentration of high-cost loans where 90 percent or more of the loan was financed. By contrast, just 12.9 percent of high cost loans were associated with tract loan-to-values of less than 50 percent.

Table 5: Ratio of Loan Amount to Median Home Value in Census Tract

Ratio of loan amount To median home value in tract	**Number non-high cost loan**	**Number high cost loan**	**Total loans**	**Percent high cost loan**
Under 50.0%	331,836.5	48,962.0	380,798.5	12.9%
50.0% to 69.0%	304,771.8	59,606.0	364,377.7	16.4%
70.0% to 89.0%	277,707.1	74,773,5	352,480.6	21.2%
90.0% to 99.0%	84,724.2	29,004.7	113,728.9	25.5%
100.0% or greater	178,862.2	53,485.7	232,347.9	23.0%

Source: Combined HMDA-PFF-ACS

One conclusion that might be drawn from this is that borrower ability to repay was likely a factor not simply where a greater share of a home purchase was financed, but in the fact that high cost loans were more likely to be made to borrowers financing nearly all of a home's purchase price.

This finding would be expected given the increased risk associated with financing proportionately more of the value of the home, saddling the borrower with a greater liability, particularly in the event of home price depreciation or job loss, increasing the probability of default. As the housing and financial crisis revealed, this is precisely what happened to so many overleveraged borrowers.

Finally, the ratio of applicant income (from HMDA) relative to median household income at the census tract level reveals a comparatively weaker relationship to the distribution of high cost loans and pre-foreclosure filings (Tables 6 and 7). The significance of income as measured in this way may be somewhat obscured by the fact that many census tracts tend to be more homogeneous. This trend finds support in several studies. Iceland and Steinmetz (2003) for instance, characterize census tracts as being relatively homogeneous with respect to population in terms of economic status and living standards. Thus, there is likely not to be the kind of large observable disparities in income that would be seen at a broader level of analysis, such as at the MSA level. This characteristic of census tracts appears to be reflected in the distribution of both pre-foreclosure filings and high cost loans at nearly all ratios of applicant income to median census tract household income.

One interesting observation is that even at high ratios of applicant income to median tract income, there are still some high cost loans At all ratios of applicant income to median tract income, the percentage of high cost loans shows little variance, ranging from 17.8 percent where the income ratio is less than 50 percent to 19.9 percent where applicant income is between 250 and 299 percent of median tract income.

Table 6: Pre-foreclosure Filing by Ratio of Applicant Income to Median Household Income in Tract

Ratio Applicant Income to Median Household Income in Tract	Number Non PFF	Number PFF	Total loans	Received PPF	Ratio high cost loans to defaults
Less than 50.0%	62,507.9	3,754.7	66,262.6	5.7%	3.14
50.0% to 99.0%	424,256.0	32,085.7	456,341.6	7.0%	2.47
100.0% to 149.0%	388,347.2	34,930.2	423,277.3	8.3%	2.29
150.0% to 199.0%	199,493.4	18,659.8	218,153.2	8.6%	2.25
200.0% to 249.0%	97,086.8	9,329.9	106,416.7	8.8%	2.24
250.0% to 299.0%	53,198.2	5,233.8	58,432	9.0%	2.22
300.0% and higher	103,736.6	9,898.8	113,635.3	8.7%	2.07

Source: Combined HMDA-PFF-ACS

Table 7: High-cost loan by Ratio of Applicant Income to Median Household Income in Census Tract

Ratio Applicant Income to Median Household Income in Tract	Number non-high cost loan	Number high cost loan	Total loans	Percent high cost loan
Less than 50.0%	53,306.1	11,974.4	67,280.5	17.8%
50.0% to 99.0%	377,728.7	79,297.2	457,025.9	17.4%
100.0% to 149.0%	342,427.0	79,829.4	422,256.4	18.9%
150.0% to 199.0%	175,332.0	41,777.4	217,109.4	19.2%
200.0% to 249.0%	85,900.9	21,021.7	106,922.7	19.7%
250.0% to 299.0%	47,069.0	11,708.3	58,777.3	19.9%
300.0% and higher	92,961.3	20,489.5	113,450.8	18.1%

Source: Combined HMDA-PFF-ACS

Quite possibly, at higher income levels, there may have been a higher proportion of "jumbo" loans, which typically carry higher interest rates or that at these higher income ratios, borrowers may have been placed into higher risk categories by lenders if they were employed in high paying, yet cyclical industries. This may also offer at least a partial explanation for the slightly higher rates of default as the ratios of applicant to median tract income rise. Higher loan amounts at higher levels of income, in addition to carrying higher rates of interest, may be at higher risk of default in a declining and/or weak housing market coupled with rising unemployment.

7 CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH

The findings of this analysis incorporating census tract data into the matched HMDA-PFF data file provide a considerably more comprehensive picture of the relationship between community characteristics and the distribution of both high-cost loans and pre-foreclosure filings at the height of the housing boom. The additional information drawn from census tract characteristics clearly indicates that the share of both high-cost loans and pre-foreclosure filing notices tended to be greater in census tracts characterized by higher poverty rates, lower employment-population ratios, and where the loan-to-value ratio was very high. These data lend fairly robust support to the argument that there is a strong correlation between loan characteristics and the demographic characteristics of the communities within which borrowers live.

The findings also raise the question of the potential significance of other demographic characteristics that could be explored in a future study. For instance, it is likely that the level of educational attainment is closely related to employment to population ratios, which would offer further insight into incidence of both high cost loans and default rates. The occupational make-up of communities, along with the dominant industries at the census tract level could reveal much about median incomes of communities. Household size may also be significant as loan characteristics and default probability might be expected to vary based upon the number of workers, and thus income, in a household.

The present study, lacking key demographic information on borrowers *within* the census tracts, suggests that any correlations found in the data are not sufficient to draw conclusions regarding discriminatory lending practices. However, the findings do raise some important questions that should be the focus of future research. Why for instance were the distribution of high cost loans and pre-foreclosure filings greater in census tracts characterized by higher poverty rates? Why were loan-to-value ratios greater in higher poverty census tracts?

To investigate the question of possible discriminatory lending, further inquiry would clearly need to look more closely at the relationship of variables such as the racial and ethnic composition of census tracts, a measure of the ratio of applicant income to median census tract income, and how a community's average FICO scores are related to the probability of people in minority vs. non-minority dominated census tracts receiving high cost loans. While the finding of a clear correlation between lower employment-population ratios and a higher distribution of pre-foreclosure filings and high cost loans is not surprising here, expanded research which includes an examination of employment-population ratios within census tracts based upon their predominant racial and ethnic composition might provide some added insight into lending patterns. Thus, an examination of the likelihood of default (as measured by the probability of receiving a pre-foreclosure filing) could be examined as a function of the percent in census tract below poverty level income, the percent employed within census tract (as measured by the employment/population ratio), loan to median tract home value, applicant income to median tract income, and dummy variables to identify applicants' race and ethnicity. The outcome of such an inquiry could provide a more comprehensive picture of the relationship between race, ethnicity and the probability of receiving a high-cost loan and/or a pre-foreclosure filing. Based upon one of the key findings of our previous research (Doviak and MacDonald, 2012), - that 35.1 percent of Black borrowers and 28.1 percent of Latino borrowers received high-cost loans - suggests and that establishing these connections between the characteristics of census tracts and their demographic make-up can provide some more definitive answers.

ENDNOTES

1. The pre-foreclosure filing data had its origins in December 2009, when New York State's Mortgage Foreclosure Law amended the Real Property Actions and Proceedings, inserting a provision (1306) requiring mortgage servicers to send borrowers a 90-day notice prior to commencing foreclosure proceedings on owner-occupied residential mortgages. The new law also required mortgage servicers to electronically submit the pre-foreclosure filings (PFF) to the NYSBD (now the Division of Financial Services or DFS) for the purpose of putting borrowers in touch with non-profit mortgage counselors and "to perform an analysis of loan types which were the subject of a pre-foreclosure notice." Since enforcement of the law is left to the courts, servicers have had a strong incentive to submit honest and accurate filings. When deciding what information about the loans to collect from the mortgage servicers, the DFS chose to collect information that would facilitate a matching of the pre-foreclosure filings to the corresponding HMDA loan originations. Furthermore, in its two reports analyzing the PFF data, the DFS compared the PFF data to the HMDA data to estimate the mortgage default rate by county and to compare mortgage default rates by loan amount.
2. Rugh and Massey (2010) use the term "subprime" to describe high-cost loans.

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The Status of Very Small Credit Unions after the 2008 Financial Crisis

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ABSTRACT

As banks and credit unions have become much larger, remarkably about 900 very small credit unions (less than $2 million in assets) still operated in 2011. They are close in size to "your grandfather's credit union." We compared them to large credit unions during 2007-2011, or the recent financial crisis. Topics examined included assessing loan risk, economies of scale, net worth ratios and return on assets. While some very small credit unions will continue to merge or liquidate, others will most likely continue to operate for some time due to their high average net worth ratio (19.2 percent in 2011).

INTRODUCTION

Financial institutions in the U.S. have grown in size and become fewer in number over the past several decades. In the banking industry, as of March 2011, 6,530 commercial banks existed in the U.S. But, the largest 86 of these banks held 74 percent of total banking assets (Mishkin, 2013). The credit union industry has also become more concentrated. For example, although 7,351 credit unions existed at the end of 2011, the largest 183 held over 48 percent of all credit union assets (Credit Union Report, Year-End 2011).

In this environment, remarkably, some very small credit unions continue to operate. In this paper we examine "very small" credit unions, defined as having less than $2 million in total assets. They are similar in size to the majority of credit unions that existed when credit unions were first founded largely along specific employee group field-of-memberships. Our objective is to examine changes in these very small credit unions in comparison to large credit unions following the 2008 financial crisis.

The paper is organized as follows. The overview describes the rise of credit unions in the U.S. over the last century, as they filled the void for consumers in obtaining small consumer loans. These early credit unions were very small and most members knew each other, which was beneficial in assessing risk in the absence of the quantitative methods that are used today. The literature review discusses economies of scale, which favor large credit unions, and other limitations of small credit unions, such as limited resources for professional staff that can deal with increasingly sophisticated financial products. The sample and data discussion follow.

The results section compares the very small credit unions (those with less than $2 million in assets) and the large credit unions (those with more than $250 million in assets) at two points in time, 2007 and 2011. During that period, the average asset size and membership of very small credit unions did not change much. This is not surprising because a very small credit union with a high growth rate since 2007 may no longer be in the very small credit union category in 2011. Large credit unions, on the other hand, grew in both asset size and members. Both types of credit unions experienced decreased yields on investments and loans. The average loan balance fell for very small credit unions, while it rose

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for large credit unions. Both sizes of credit unions experienced lower net worth ratios over the four-year period, but very small credit unions had much higher ratios (19.2 percent in 2011) than the large credit unions (10.2 percent). Very small credit unions had negative average ROA (return on assets) in 2011, unlike the large credit unions, and had higher operating expense-to-average asset ratios. Most surprising, however, was that very small credit unions had higher delinquency ratios and charge-offs than did their large counterparts. Small credit unions were supposed to have an advantage in assessing members' credit risk. However, that was not the case.

The conclusion notes that while very small credit unions will continue to disappear, some will hang on for a while due to their high capitalization.

OVERVIEW

At the turn of the twentieth century, unmet demand existed for small consumer loans since commercial banks and savings institutions generally specialized in other types of loans (National Credit Union Administration, 2012). Before the advent of nationwide credit bureaus, it was difficult for financial institutions to evaluate the risk of these small, unsecured loans (Walter, 2006, p. 353). As a result, many of these small, unsecured loans were made through the black market. For example, it was estimated in 1911 that about 20 percent of urban workers borrowed from illegal lenders (Walter, 2006, p. 353).

Credit unions are not-for-profit depository institutions that serve a field-of-membership, such as a community or employment group. Rather than issuing stock, they are owned by their members, each of whom has one vote regardless of the number of accounts or size of accounts that each holds. The members elect a board of directors from the membership. The directors are volunteers and are not compensated for their contributions. For a discussion of volunteer motivation in credit unions, see Ward and McKillop (2011). Wilcox and Dopico (2011) state "this structure presumably leads to different practices and performance goals than those of banks" (p. 1).

The first credit union in the U.S. was chartered in 1909 in Manchester, New Hampshire as the La Caisse Populaire Ste. Marie (Witzeling, 1993, p. 31). Credit unions helped to fill the void in small consumer loans. Credit unions were small and based on a common bond membership, usually with workers from the same firm. Loans were typically made through a credit committee and since many of the members would know each other, "they could substitute their knowledge of one another's creditworthiness for collateral" (Walter, 2006, p. 353). While banks obtained FDIC deposit insurance in 1933, credit unions operated without deposit insurance until 1970, in part because this mechanism for making loans kept credit union loan defaults more manageable.

For years credit unions remained small. For example, in 1932, the average credit union size in terms of members was just 187 (Walter, 2006, p. 354). For years, the main asset for credit unions was these small and often unsecured loans for items such as purchasing autos and appliances, paying medical bills, and making home repairs. While credit unions remained small, their numbers grew. Even during the Great Depression the number of credit unions continued to grow (Ryder and Chambers, 2009) and peaked at 23,866 in 1969 (Wilcox and Dopico, 2011, p. 1).

However, over time credit unions began to evolve. In 1970 credit unions began to offer deposit insurance (Witzeling, 1993, p. 38), similar in coverage to FDIC deposit insurance for banks. Legislation in 1977 allowed credit unions to offer real estate loans and certificates of deposit (National Credit Union

Administration, 2012). And in 1980, the Depository Institution Deregulation and Monetary Control Act allowed credit unions to offer checking deposits. Meanwhile, some credit unions already had large field-of-memberships (such as the U.S. Navy), while others increased their field-of-membership by obtaining multiple field-of-memberships or by switching to community charters. As a result of being able to offer more financial products and services, coupled with larger field-of-memberships, most credit unions began to grow in size and some became very large. While total credit unions assets and membership continued to increase, the actual number of credit unions continued to decrease mainly due to mergers along with an occasional failure. At year-end 2011, 7,351 credit unions existed (Credit Union National Association, 2011).

Yet, some credit unions remained very small. In 2003, there were 1,828 credit unions with less than $2 million in assets (Table 1.). Their number fell to 1,390 by 2007 and to 920 in 2011. This still represented 12.5 percent of all credit unions in 2011. On the other hand, 636 credit unions had assets in excess of $200 million in 2003. Their number grew to 738 by 2007 and to 865 by 2011. Thus, credit union asset size varied immensely. For example, Fryzel (2012) pointed out that in 2012 Navy Federal Credit Union had over $48 billion in assets, while Holy Spirit Baptist Federal Credit Union was tiny, with just under $14,000 in total assets.

Table 1. Credit union numbers, selected years

	Number Credit unions with less than $2 million in asset size	**Number of credit unions with more than $200 million in asset size**
2003	1,828	636
2007	1,390	738
2011	920	865

Source: Credit Union Report, Year-End 2003, 2007, and 2011.

There is no standard definition of the asset size for small and large credit unions. For example, Wilcox (2005) defines small credit unions as less than $100 million in asset size and large credit unions as greater than $1 billion. As of 2012, the National Credit Union Administration classified small credit unions, which are exempt from certain regulations, as having assets less than $10 million (Anderson, 2012). For this study, we classify “very small” credit unions as having less than $2 million in asset size. These credit unions are close in size in terms of members to the average credit union that existed in the past, i.e., your grandfather’s credit union. We classify “large” credit unions as having assets greater than $250 million. After a brief literature review, we present a comparison of these very small and large credit unions in 2007 and in 2011, before and after the 2008 financial crisis. Due to limitations in our Peer-to-Peer credit union data source, we can only compare the same very small and large credit unions that existed at year-end 2011. In this sample, the “very small” credit unions number 889, the “large” credit unions number 726. Each group represented approximately 10-12 percent of the total number of credit unions.

LITERATURE REVIEW

The literature on credit union size tends to focus on cost differences. Not surprisingly, larger credit unions tend to have cost advantages due to economics of scale. The only advantage that smaller credit unions may have is due to the fact that since they are small, they know their members better, which results in a better screening for creditworthiness (Walter, 2006).

Some authors using the same reasoning argue that credit unions, being smaller institutions on average than banks, may have the same creditworthiness advantage. This could potentially translate into an advantage for small credit unions relative to large ones. Wheelock and Wilson (2011, p. 1343) wrote that a “common bond is advantageous because it can reduce the cost of assessing the creditworthiness of potential borrowers and thereby facilitate lending on reasonable terms.” However, they also state (p. 1343) that “recent advances in information processing and communications technology have lowered the cost of acquiring hard information about potential borrowers, and thereby have eroded some of the advantages of small scale and common bond.” Klinedinst (2010) suggested that credit unions, being on average a smaller depository institution, might have an informational advantage because they know their members well and “this information advantage may help to potentially offset the relative lack of scale efficiencies” (p. 56).

A number of studies have found significant economies of scale advantages for larger credit unions. In particular, advances in information processing and technology and a series of legislation and new regulations have been major sources for these economies of scale. Kohers and Mullis (1988) discussed studies from the 1970s and 1980s that found conflicting results on economies of scale for credit unions, but their own analysis found evidence of economies of scale using NCUA data from 1984.

Massachusetts charters cooperative banks (CBs) that are similar to credit unions because they are cooperatives and relatively small in size for a depository institution. Rezvanian, Mehdian and Elyasiani (1996), using a set of translog cost functions for CBs for the years 1989-91, found “that scale economies were present for CBs of all sizes over the three year period” (p. 51).

Wilcox (2005, p. 1) wrote that “larger credit unions, on average, have decidedly lower costs,” and that these economies of scale led to a continued industry consolidation, resulting in fewer, but larger credit unions. He showed that noninterest expense as a percent of assets decreases by about 0.5 percent as credit union asset size increases from $1 million to $10 million. Then it stayed about the same as credit unions increased to $100 million, but decreased about another 1.0 percent as credit unions grew to over $1 billion in asset size (p. 1). These cost differences may be even further disguised as smaller credit unions may offer “fewer products and services as a way to contain costs” (p. 2). Wilcox also showed that as credit union asset size increases, their cost advantages allowed them to pay higher interest rates on deposits (p. 2), while they charged lower interest rates on loans (p.3), and earned higher net incomes (p. 2). However, the larger credit unions charged higher fees than the smaller credit unions (p.4).

Wilcox (2006) used data from 1980-2004 to show that there was an “increasing performance divergence over this period” (p. 1), favoring larger credit unions with respect to noninterest expenses, return-on-assets, and interest expense. While credit union consolidation continued, Wilcox stated that it was unlikely that the industry would be “dominated by a few nationwide institutions any time soon” (p.3). This was because credit union field-of-membership is still restricted to community, employer group(s) and association by legislation and that the “costs at many small credit unions are low enough to keep them competitive” (p. 3).

Wheelock and Wilson (2011, p. 1356) wrote that “we are unaware of studies investigating returns to scale rigorously for credit unions.” They found, using 1989-2006 data and a nonparametric local-linear estimator, that there existed both ray-scale and expansion-path economies of scale for credit unions. They concluded that “as of 2006, most credit unions were too small to fully exploit possible economies of scale” (p. 1358).

The prevalence of economies of scale in the credit union industry has led to efficiency benefits for small credit unions that are acquired by larger ones. Wilcox and Dopico (2011) studied noninterest expense changes resulting from credit union mergers during 1984-2006. For all mergers, the average size of the targeted credit unions was $7.0 million in asset size, while the average size of the acquirers was $159.4 million. For the group as a whole, the targets showed an average reduction of 0.79 percent in noninterest expense/assets, while the acquirers saw no change (p. 3).

Lastly, as financial products and their delivery become more sophisticated, smaller credit unions became constrained by their employees and volunteer board members. Goddard et al. (2008) discussed different philosophies of credit unions. Some are guided more closely by the cooperative vision of the early credit union movement, where credit union members would actively participate in the management of the credit union. They wrote that these credit unions "would never achieve the size or level of financial sophistication whose governance would be beyond the capacities of ordinary members" (p. 889). However, other credit unions have grown and offer a wide array of financial products. "They do not rely on volunteers, but are operated by professional and qualified management staff" (p. 889). Wilcox and Dopico (2011, p. 4) also state that as credit unions grow in size and product offerings, that they "are increasingly managed by professionals instead of volunteers."

SAMPLE AND DATA

Data on all U.S. credit unions from all 50 states, Washington D.C., Puerto Rico, and Guam were obtained from Callahan and Associates' Peer-to-Peer (2011). This database includes information contained in the NCUA's 5300 Call Report. Only credit unions that were active in the last quarter of 2011 reporting cycle were available for analysis from this data source. Hence, credit unions that were active in 2007 but have since merged with other credit unions or become inactive are not included in our analysis as they are no longer available from the Peer-to-Peer data. Also, only retail credit unions and not corporate credit unions are included in the Peer-to-Peer data.

We defined very small credit unions as those with less than $2 million in assets, of which there were 889 in the Peer-to-Peer data set at year end 2011. The 726 large credit unions in the sample are those we defined with more than $250 million in assets. Values for 2007 and 2011 are for year-end.

Paired-t tests were used to test for significant differences in characteristics of these credit unions between 2007 and 2011.

RESULTS

The effect of the financial crisis on credit unions was striking. Tables 2 and 3 compare key measures for the 889 very small credit unions and 726 large credit unions in 2007 and 2011. Most of these measures, including membership, the loan-to-asset ratio, the net worth ratio, and return on assets changed significantly over the course of the financial crisis. In addition, very small and large credit unions display markedly different characteristics in these key measures.

Size and Membership. Table 2 shows that the size of the very small credit unions had a statistically insignificant increase from $881,626 to $899,672, while the average membership showed a significant decrease of 24, to 357. These small numbers are not surprising since a very small credit union that had a high growth rate since 2007 may no longer be in the very small credit union category in 2011.

On the other hand, the large credit unions experienced a statistically significant increase in both asset size and membership. Size increased by $253,547,751 to over $1 billion, while membership increased by 11,310 to reach 85,847. A small part of this increase in average size for large credit unions could have come from some credit union mergers. Wilcox and Dopico (2011) studied credit union mergers during 1984-2006. The average size of the acquiring credit union in their sample was much larger at $159.4 million, while the average size of the acquired credit union was much smaller, at $7.0 million. Also, many large credit unions were neither interested nor involved in mergers during 2007-2011. Hence, the vast majority of the large credit union size increase likely came from internal growth. This included new membership as well as credit union members that stayed away from the stock and real estate markets and put money in their credit union accounts. Consequently, liability growth led to asset growth on the other side of their balance sheets.

Table 2. Mean assets, members, loan/asset ratio, loan and deposit balance, yield on investments, yield on loans, cost of funds, 2007 and 2011.

	Very Small (< $2 million assets)		Large (>$250 million assets)	
	2007	2011	2007	2011
Total assets	$881,626	$899,62	$764,454,904	$1,018,002,655
Members	381	357*	74,537	85,847*
Loan-to-asset ratio	50.8%	43.8%*	69.8%	59.9%*
Yield on investments	3.8%	0.8%*	4.8%	1.5%*
Yield on loans	8.6%	8.5%+	6.7%	5.7%*
Cost of funds / average assets	1.90	0.75*	3.08	0.97*
Average loan balance	$5,039	$4,832+	$14,573	$16,284*
Average deposit balance	$2,066	$2,285*	$8,642	$10,761*

*Significant difference from 2007 levels (α = .05)
+Weakly significant difference from 2007 levels (α = .10)

Assets and Liabilities. Very small credit unions tended to have lower loan-to-asset ratios than larger credit unions, both at the beginning and end of the financial crisis. In 2011, very small credit unions had an average loan-to-asset ratio of 43.8 percent, as compared to a ratio of 59.9 percent for large credit unions (see Table 2.). Both size groups experienced a significant decrease in this ratio between 2007 and 2011.

Very small credit unions' loan-to-asset ratio fell from 50.8 percent in 2007 to 43.8 percent in 2011. This low loan-to-asset ratio for very small credit unions presents a mixed outlook for their expected future net income. On one hand, the very small credit unions operate with more of their assets in investments, which yielded historically low returns in the post 2008 financial crisis years. On the other hand, a smaller percentage of their assets in loans imply, other things equal, fewer charge-offs.

Note that both groups of credit unions generally experienced statistically significant decreases in their yields on investments and loans, as well as their cost-of-funds during 2007-2011. By 2011, the average yield on investments for the very small credit unions was only 0.8 percent, or about half of the yield for large credit unions, which tend to have more sophisticated investments in place. For the very small credit unions, these low investment rates, coupled with their relatively low loan-to-asset ratio, had a negative influence on their net income. Also note that the large credit unions charged their members less on loans and paid more on deposits than the very small credit unions. Wilcox (2005, p. 3) had found similar results for credit union interest rates on loans and deposits. However, due to decreasing yields on loans and investments, coupled with increasing loan charge-offs, the large credit unions have lowered their deposit rates more than the very small credit unions during 2007-2011, so that the difference dropped from 1.18 percent in 2007 to only 0.22 percent in 2011.

Both the very small and the large credit unions saw statistically significant increases in their average deposit balances, probably due in part to members selling some of their stock market investments and making a "flight to safety" to the insured credit union accounts. However, while large credit unions also experienced a significant increase in their average loan balance, the very small credit unions experienced a decrease. The large credit unions have both average loan and deposit balances that are about 3 to 5 times greater than they are for the very small credit unions, undoubtedly a source of economies of scale.

Key ratios. Table 3 reports six different key financial ratios. The table shows that net worth ratios (essentially the same as capital-to-asset ratios) fell significantly for both groups of credit unions between 2007 and 2011. The size of the net worth ratio is of interest, since there was a trend before the financial crisis for increasing net worth ratios. For example, the average net worth ratio of the U.S. credit union industry was 11.6 percent in 2006, up from 7.6 percent in 1990 (Jackson, 2007). Of special interest, however, is the difference in size of the net worth ratios for these two groups. Very small credit unions had a very high average net worth ratio of 20.9 percent in 2007, which fell by a small amount to 19.2 percent in 2011. Large credit unions ended this period with net worth ratios of 10.2 percent. This concurs with Goddard et al. (2008), who found that capital-to-asset ratios and asset size to be inversely related. Since the National Credit Union administration defines a credit union with a net worth ratio above 7 percent to be "well capitalized," both groups remained well capitalized on average.

Table 3. Mean net worth ratio, return on assets, non-interest income, operating expense, charge offs/loans and delinquency ratio of loans, 2007 and 2011

	Very Small (< $2 million assets)		Large (>$250 million assets)	
	2007	2011	2007	2011
Net worth ratio	20.9%	19.2%*	11.7%	10.2%*
Return on assets (ROA)	.87%	-.35%*	.74%	.66%*
Non-interest income / average assets	1.0%	1.1%	1.5%	1.4%*
Operating expense/average assets	4.3%	4.5%*	3.6%	3.4%*
Charge offs	1.03	1.17	.46	.86*
Delinquency ratio	6.1	6.4	.8	1.5*

*Significant difference from 2007 levels (α = .05)

Given the prevalent economies of scale for credit unions, it was surprising that the return on assets (ROA) was higher for very small credit unions than for large credit unions in 2007, .87 versus .74. It could be that the remaining very small credit unions are careful in managing their expenses in categories such as salary restraint, plain vanilla product offerings, careful loan underwriting, and charging higher interest rates on loans (see Table 3). Also, some very small credit unions sometimes have access to subsidized land or office space.

However, this pattern reversed over the next four years. As ROA for large credit unions fell to .66, it fell further and became negative at -0.35 for very small credit unions. Both of these changes were statistically significant. It appears that the excessive capital held by very small credit unions helped them survive the financial crisis with a strong net worth ratio, even as their ROA became negative.

Table 3 shows that the very small credit unions have much lower non-interest income/average assets than the large credit unions. Part of this could be because the very small credit unions offer fewer services/products, many of which charge fees. But, everything else equal, the larger credit unions seem to charge higher fees. Wilcox (2005, p. 3) pointed out that this is one advantage for members of smaller credit unions versus larger credit unions. Although increases in fee income boost revenues, some studies have found that higher proportions of fee income are correlated with higher levels of risk; see for example Esho et al. (2005).

Table 3 also shows that the operating expenses-to-average assets are about one percentage point higher for the very small relative to the large credit unions. We did expect this with the prevalent economies of scale in the credit union industry. Even more telling, while the operating expenses-to-average assets ratio increased by a statistically significant amount during 2007-2011 for the very small credit unions, it significantly decreased for large credit unions.

Loan losses. Very small credit unions had a higher rate of loans being charged off than did large credit unions. Charge offs rose slightly, but not significantly, for very small credit unions between 2007 and 2011, from 1.03 to 1.17 (see Table 3). This is a higher rate of charge offs than for the large credit unions, which experienced a statistically significant rise, from .46 to .86. Although it is believed that very small credit unions, with relatively small number of members, should be better able to judge the creditworthiness of their loan applicants, this does not appear to be the case, both before and after the financial crisis.

Similarly, the delinquency ratio of loans of very small credit unions was higher than that of large credit unions. This ratio rose only slightly for small credit unions, from 6.1 to 6.4, while it rose significantly for large credit unions, from .8 to 1.5 over the four-year period. Even though the delinquency ratio rose significantly for the large credit unions, the ratio remained much smaller than that of the very small credit unions.

Product offerings and rates. Very small credit unions also differ from large credit unions in the types of products they offer members. Very small credit unions have limited resources to offer credit cards and mortgage loans, as well as money market or certificates of deposit. The number of credit unions offering various loans and deposits are shown in Table 4.

Very few of the very small credit unions offered credit card or mortgage loans, while nearly all of the large credit unions reported offering mortgage loans and about 87 per cent offered credit cards. There was a trend in the early 2000’s for some credit unions to sell off their credit card portfolios and then partner with a credit card provider (often a bank) to offer credit cards to their members. In addition, large credit unions, probably due to economies of scale, offered significantly lower loan rates than the very small credit unions.

Table 4. Percent of credit unions offering loans and corresponding rates, 2011

Type of loan or share	Very small credit unions		Large credit unions	
Account	Percent Offering	Rate (%)	Percent offering	Rate (%)
Credit card	2.4	12.9	87.4	9.9
New vehicle loan	64.0	5.5	99.7	3.8
Used vehicle loan	74.0	7.0	99.4	4.3
First mortgage	4.9	6.7	99.9	4.2
Other real estate loan	6.6	6.5	100	5.0
Checking deposits	7.0	0.0	99.6	0.2
Regular savings deposits	100	0.6	100	0.3
Money market accounts	1.6	0.7	92.6	0.4
Certificates of deposit	22.0	1.1	98.8	0.9

Most of the large credit unions offered the array of deposit accounts shown in Table 4. All very small credit unions offered regular savings accounts, and a substantial number offered certificates of deposit, but few offered checking or money market accounts. Rates offered on all of these accounts were very low for both types of credit unions in 2011.

Field of membership. Very small credit unions also differ from other credit unions in that they tend to serve specific employer and industry groups rather than communities. Table 5 reports the number of credit unions by size for several fields of membership. Credit unions with fields of membership designated as “other” and “employee group” are not included, since they did not fit into a clear field-of-membership category.

Table 5. Credit Union Field-of-Membership by Size Category

Field of Membership	Very Small (<$2 million)	Large (> $250 million)	Total for all US credit unions
Educational	51	3	186
Associational	213	5	352
Community	36	148	1071
Government	39	9	279
Manufacturing	80	4	249
Service	54	10	292

Educational, associational, manufacturing, and service industry credit unions are heavily represented in the population of very small credit unions. Of the 186 credit unions with an educational field of membership, 51 (27 percent) are very small, as are 60 percent of associational, 32 percent of manufacturing, and 18 percent of service industry credit unions. Very large credit unions are heavily represented in the community category. In fact, many credit unions converted to community charters during the 1990’s and 2000’s, seeking growth by serving larger field-of-memberships. Thus, members of small credit unions tend to be concentrated in small employee groups, very similar to the early credit unions. These members often know each other as well as board members and the credit union staff, which creates a sense of credit union loyalty and association. On the other hand, members of large credit unions have a large field-of-membership and often have a community charter, which greatly reduces their sense of credit union loyalty and association. They often view themselves as “customers” rather than “members.”

CONCLUSION

Both the banking and credit union industries have been experiencing significant consolidation in recent years. As depository institutions are becoming much larger on average, it is interesting to note that there still existed about 900 “very small” credit unions (defined in this paper with assets under $2 million) at year-end 2011. These very small credit unions may have one advantage over larger competitors. Due to their small size, they may be able to better assess the credit risk of their members. This possible advantage, which may have been significant in the past, is probably relatively small today since a borrower’s risk can be economically assessed with information technology. However, we found that the very small credit unions did have higher ratios for both loan charge-offs and delinquency in comparison to the large credit unions, although it was the large credit unions that saw a statistically significant increase in both.

The literature concludes that significant economies of scale exist over a wide range of credit union asset sizes that create a substantial disadvantage for small credit unions. In addition, the very small credit unions typically would not have qualified management/boards needed to grow and offer new products even if they wanted to.

The number of very small credit unions has been declining since the 1970s, and their numbers at year-end 2011 are about half of what they were in 2003. The numerical decreases were about the same in 2003-2007 as in 2007-2011, although the rate of decline was faster during the later period. And, this decline will undoubtedly continue as economies of scale remain prevalent. Yet, a number of very small credit unions will continue to exist for a while. How did these remaining very small credit unions perform during the 2008 financial crisis?

The very small credit unions still operating in 2011 had an average asset size of $0.9 million, while their average membership stood at 357. These are extremely small numbers today for a depository institution. This is also very similar to the size of your grandfather’s credit union. The loan-to–asset ratio was lower for the very small credit unions in comparison to the large ones, although both saw significant decreases in this ratio. The very small credit unions in 2011, as is 2007, earned a higher yield on loans than larger credit unions, while they earned a lower yield on investments and had lower cost-of-funds/assets. During 2007-2011, the difference between the very small and large credit unions in yield on investments dropped a little to 0.7 percent, while the difference in cost-of-funds dropped substantially to 0.22 percent.

Surprisingly, relative to the large credit unions, the very small credit unions had a higher ROA in 2007. While both groups experienced a statistically significant drop in ROA during 2007-2011, the ROA for the very small credit unions fell to a minus 0.35 percent. The remaining very small credit unions were able to ride out a negative ROA due to their very high net worth ratio, which still stood at 19.2 percent at year-end 2011. Relative to the larger credit unions, the very small credit unions had smaller non-interest income/average asset ratios, indicating probably lower fees, but they had much higher operating expense/average asset ratios, indicating prevalent economies of scale.

The very small credit unions remained very plain vanilla in what they offered in terms of products, again similar to your grandfather’s credit unions. On their asset side, they concentrated on making consumer loans, including auto for most. But unlike the large credit unions, they generally stayed away from mortgage and credit card loans. On their liability side, they concentrated on the plain vanilla savings account deposits, while few offered certificates of deposit and checking deposits. Lastly, the very small credit unions are heavily represented in educational, associational, manufacturing, and service industry, with only 36 having strictly a community field-of-membership.

The very small credit unions will continue to decline in numbers. However, some will probably remain in operation while not growing much in the coming years. Since the remaining very small credit unions are still highly capitalized, they can operate for a number of years with lean or even negative ROAs. And, their average ROA was quite good in 2007, before the crisis. Since they have a relatively low loan-to-asset ratio, they depend more on their investment income. As the economy recovers, their investment income should return to more normal levels, which will help their ROAs. But they will continue to lack economies of scale and also will probably offer less competitive interest rates to their members. The future life span of the very small credit unions remaining will ultimately depend on the continued loyalty of their volunteers and membership.

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Cohort Analysis Of U.S. Consumer Bankruptcy

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ABSTRACT

This paper examines how the effects of the aging process, period-specific events, and birth cohorts explain U.S. consumer bankruptcy filings, based on secondary data from the Institute for Financial Literacy (IFL) and the American Association of Retired Persons (AARP). Bankrupt consumers are divided into five age classes and eight ten-year cohorts, and investigated over four ten-year periods, using data from 1970 to 2010. The results showed that the birth-cohort effect was the most predominant predictor. There was a significant aging-process effect too. The period-specific effect merely reinforced both cohort and age effects. In addition, the results showed that the baby-boomer generation, born between 1947-1966, experienced the largest cohort effects in relation to other generations; also, they experienced the largest increases in bankruptcy filings in comparison to preceding generations. The X generation, born between 1967-1976, experienced the largest age and period effects. Interestingly, the millennial generation, born between 1977-1996, experienced the lowest bankruptcy filings compared to when preceding generations were in the same age bracket.

1. INTRODUCTION

Bankruptcy is a process in which consumers can eliminate some or all of their debts under the protection of the federal bankruptcy court. For the most part, formal bankruptcy proceedings may entail a liquidation process and a reorganization process (Senbet and Seward, 1995). Over the last four decades, there have been noticeable increases in percentage rates of U.S. consumer bankruptcy filings and a recent study by Gross et al. (2013) even suggests that the number of filers would be higher were it not for the legal and administrative fees associated with the filing process. According to Sullivan and Warren (1999), available records suggest that recent bankruptcy filings are fueled by divorced, widowed, and single women and medical problems. (See also Himmelstein et al., 2009; Warren et al., 2000). Sometimes, the reason for the default can be loss of a job and overspending (Zywicki, 2005) on durables such as automobiles and houses (Zhu, 2008), credit-card defaults (Gerhardt, 2009), high indebtedness and business cycles (Bishop, 1998), as well as changes in the in the credit market environment (Livshits et al., 2010).

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Yet, this spike in bankruptcy filings over the last four decades is quite staggering given that total U.S. consumer bankruptcies increased from 199,500 in 1970 to 1,536,799 in 2010. Even though there is historical evidence showing that massive bankruptcy filings also occurred in the United States in the 19th century (Warren, 1935), the magnitude of the recent increases in percentage rates of bankruptcy filings merits a closer investigation, and that is the goal of this study.

In particular, this study investigates whether consumers' age, period-specific events that happened during the study period, and birth cohorts might help explain this noticeable spike in percentage rates of U.S. consumer bankruptcy filings. A suitable research methodology for exploring this research question is a cohort analysis, which can be used to estimate the age, period, and cohort effects on a dependent variable such as the U.S. consumer bankruptcy filings. Therefore, this study adopts the constrained multiple regression for the estimations. The null hypothesis is that the three independent variables of age class, periodic event, and birth cohort have no effects on the U.S. consumer bankruptcy filings from 1970 to 2010.

There are two key contributions of this study. First, the study is yet another example, using data on U.S. consumer bankruptcy filings that shows the efficacy of the constrained multiple regression method in cohort analysis as pioneered by Mason et al. (1973). In the literature, Mason et al.'s model is considered to be a special case of Friendberg et al.'s (1978) model and Nakamura's (1986) Bayesian cohort model. Thus, using Mason et al.'s constrained multiple regression method, this study showed that, of the three predictors under study, the cohort effect had the most significant influence on consumer bankruptcy filings and that the age effect was also significant. The period effect was found to reinforce the impacts of cohort and age effects on U.S. consumer bankruptcy filings during the study period. Also, the study found that the baby-boomer generation, born from 1947 to 1966, experienced the largest cohort effects of the generations under study. The same baby-boomer generation experienced the largest increases in bankruptcy filings in comparison to preceding generations. The X generation, born between 1967 and 1976, experienced the largest age and period effects, while the millennial generation, born between 1977 and 1996, experienced the lowest level of bankruptcy in comparison to when the preceding generations were in the same age bracket.

Apart from the above theoretical contribution, the second contribution of this study is that, given the findings that belonging to a particular birth cohort and age class significantly affected U.S. consumer bankruptcy filings, it provides additional empirical evidence in support of structuring financial products by age class and, potentially, birth cohort. Investopedia.com reports that there are already financial products, such as life cycle or age-based funds in the mutual and retirement fund sectors that are structured by age class. So, in light of this study's findings, the author suggests that financial planners should consider structuring financial products by birth cohort.

This study is structured in the following way. First, it discusses the legal framework underlying the U.S. consumer bankruptcy. Second, the study presents a brief review of the literature on cohort studies. Third, in descending order, it presents sections on the model specification, data sources and variable descriptions, as well as interpretations of estimation results. Lastly, the study closes with concluding remarks.

2. **LEGAL FRAMEWORK FOR THE U.S. CONSUMER BANKRUPTCY**

The legal framework underlying the U.S. consumer bankruptcy can be traced back to the 1800s. Notable consumer bankruptcy laws include the 1800, 1841, 1867, 1898 laws (Garrett, 2007). The 1898 law was the basis of the consumer bankruptcy system in the United States until 2005. Today, American consumers can choose between two bankruptcy procedures: Chapter 7 and Chapter 13. Under Chapter 7, all unsecured debt is discharged in exchange for non-collateralized assets above the exemption level. Debtors in Chapter 7 are not permitted to re-file under chapter 7 for six years, although they may file for chapter 13. Approximately 70 percent of consumer bankruptcies are filed under Chapter 7. According to Bankruptcy Basics (2011, p.35), a publication of the Administrative Office of the United States Courts, filers must pay the bankruptcy court filing fee and the cost of legal advice. Chapter 13 on the other hand permits debtors to keep their assets in exchange for a promise to repay part of their debt over the next 3 to 5 years. The debtor's plan must repay unsecured creditors at least as much as they would have received under a Chapter 7 filing. The plan has to be confirmed by the bankruptcy judge, but creditors cannot block the plan. In the 1960s, Congress considered several bills that would bar from Chapter 7 those debtors with the ability to pay, but rejected them.

Then a congressional bankruptcy review commission, reporting in 1973, concluded "that forced participation by a debtor in a plan requiring contributions out of future income has so little prospect for success that it should not be adopted" (Fay et al., 2000). Following this lead in the 1978 overhaul of the U.S. bankruptcy law, Congress declined to force supposed "can pay" debtors into involuntary payment plans, which shows that the personal bankruptcy law was favorable for individual debtors (White, 1998).

In 1984, at the behest of credit-industry lobbyists, Congress added a new rule providing the bankruptcy court the power to dismiss the Chapter 7 case of an individual debtor whose debts were primarily consumer debts, if the court found that the filing was a "substantial abuse" of Chapter 7. Further intense efforts finally resulted in the enactment on April 20, 2005, of the Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA) of 2005 (Brown and Ahern, 2006). The new law favors creditors. For example, credit card companies are now given the ability to claim credit card fraud against debtors for smaller sums of money (Molleur, 2006). The law prevents quick resolution of bankruptcy cases (Brown and Ahern, 2006) by requiring pre-filing credit counseling, imposing new liabilities and responsibilities on consumer bankruptcy attorneys that drive up the costs of filing and prosecuting consumer bankruptcy cases, and imposing a means-test to determine whether a given Chapter 7 bankruptcy filing is abusive and must be dismissed or converted to Ch.11 or 13- both of which offer less relief to the debtor.

As reported by CCH Incorporated (2005), the protections offered to debtors in the BAPCPA include uniform definition of domestic support obligations for priority, discharge, exemptions, and lien avoidance; first priority for domestic support obligations; priority treatment to claims assigned to governmental units; maintenance of current support as a condition for confirmation and discharge; expanding exceptions to the automatic stay to permit support collections; and requiring trustees to provide support claimants with specified notices.

With regard to the impact of the new law, Flynn (2014) shows that 5 million fewer consumer bankruptcies were filed than would have been the case without the law. The reasons for the fewer bankruptcy filings include increased cost to file, mandated credit counseling, required tax returns, public perception, and ‘thousands of paper cuts.’ In the following section, the study presents a brief literature review of the literature on cohort studies.

3. BRIEF LITERATURE REVIEW OF STUDIES ON COHORT ANALYSIS

A cohort may be defined as the aggregate of individuals (within some population definition) who experienced the same event within the same time interval (Ryder, 1968; Rosow, 1978). Cohort analysis can be any quantitative research that uses a measure of the concept of cohort and relates that measure to one or more additional variables (Glenn, 2005). The cohort as an analytic entity appears in the social sciences, the life sciences, and epidemiology.

There is a cohort study by Balleer et al. (2009) which shows that the increasing labor participation depends significantly on both age and cohort effects. Hsueh and Yen (2009) show that the highest homeownership rate and lowest amount of living space per person occur in middle age. Halverson (2003) shows statistically insignificant differences in household savings among birth cohorts. Other notable studies include: Borjas (1985) which shows a decline in the ‘quality’ of immigrants; Bratti (2002) shows that family income has a statistically positive impact on cohorts, even though long-term family characteristics have more profound impact; Kock et al. (2012) show that age cohort can affect retirement planning; and Pencavel (2000) shows that uncompensated wage elasticities for men are small, and perhaps negative. Critics of the efficacy of cohort analysis, including Saski and Suzuki (1987) and also Frienberg and Mason (1978), point to an identification problem, in which the three variables of age, period, and cohort, as usually measured, are confounded with one another.

In light of that, the key issue in the literature centers on how to get around the confounding problem (Glenn, 1987), including the effects of influences associated with aging and cohort membership. One approach is to view the age, period and cohort effects as proxy variables for intractable real-economy variables (Heckman and Robb, 1985). Another approach is to estimate the age and cohort effects with some small-order polynomials, even though they may be unable to accurately capture trend breaks (Japelli, 1999). Suggested studies on how to get around the confounding issues include Mckenzie (2005) which employs second differencing to identify the age, period, and cohort problem; Winship and Harding (1976) and also Browning et al. (2012) use the maximum-entropy principle to overcome the point identification inherent in the linear age-period-cohort model; Glenn (1977) uses visual inspection; Agnello (1973) adopts 'correct' for period effects; Schaie (1965) uses sequential strategies; and Palmore (1978) as well as Rentz and Reynolds (1981) use the triad method. Other notable works on cohort analysis include Mason and Fienberg (1985), Mason and Wolfinger (2002), Yang, (2007), Yang et al. (2008), and (Glenn, 2005). Next, this study discusses the theoretical framework of the age-period-cohort model.

4. AGE-PERIOD-COHORT ANALYSIS MODEL

This section explores the specific model selected for this study, which is the constrained multiple regression. Below, by indicating that the dependent variable Y is a function of three independent variables of A, P, and C, the basic cohort model can be represented:

$$Y = f(\mathrm{A}, \mathrm{P}, \mathrm{C}) \qquad \mathbf{(1)}$$

where Y is the dependent variable and A, P, and C represent the effects on Y of age classes, periodic economic events (such as GDP, stock markets etc.), and birth cohorts, respectively. In a generalized form, the cohort model can be written like this:

$$Y_{ijk} = \mu + \sum_{i=1}^{\mathcal{I}} \mathrm{A}_i + \sum_{j=1}^{\mathcal{J}} \mathrm{P}_j + \sum_{k=1}^{\mathcal{K}} \mathrm{C}_k + \mathcal{E}_{ijk}, \ \ with \sum_{i=1}^{\mathcal{I}} \mathrm{A}_i = 0, \sum_{j=1}^{\mathcal{J}} \mathrm{P}_j = 0, \sum_{k=1}^{\mathcal{K}} \mathrm{C}_k = 0 \qquad \mathbf{(2)}$$

Equations 1 and 2 indicate that variable Y_{ijk} is a linear function of the age effects, the period effects, and the cohort effects. The μ is the overall mean, the A_is are the age effects, the P_js are the period effects, the C_ks are the cohort effects, and $\mathcal{E}_{ijk}$ the random error which is assumed to be normally distributed with a mean 0 and variance $S^2{}_e$. The expected value can be represented as:

$$\mathbf{E}(\boldsymbol{Y}) = \mu + \mathrm{A}_i + \mathrm{P}_j + \mathrm{C}_k \qquad (3)$$

Equation 3 indicates that the A_i, P_j, and C_k are the deviations from the mean due to aging, the effects of events that happened during at specific time periods, and cohort membership. They are the parameters to be estimated. The interactive effects of A_i, P_j,, C_k,, and ε_{ijk} can be generalized in a nonlinear equation form (Rust and Yeung, 1995):

$$\text{M}inimize\ h = \text{M1}\Big[\sum_{i=1}^{\mathcal{I}}\mathcal{A}_{i^2} + \sum_{j=1}^{\mathcal{J}}\text{P}_{j^2} + \sum_{k=1}^{\mathcal{K}}\text{C}_{k^2}\Big] + \text{M2}\Big[\big(\sum_{i=1}^{\mathcal{I}}\mathcal{A}_{i^2}\big) + \big(\sum_{j=1}^{\mathcal{J}}\text{P}_{j^2}\big) + \big(\sum_{k=1}^{\mathcal{K}}\text{C}_{k^2}\big) + \big(\sum_{j=1}^{\mathcal{J}}\text{P}_{j^2}\big)\big(\sum_{k=1}^{\mathcal{K}}\text{C}_{k^2}\big)\Big] +$$

$$+\text{M3}\Big[\big(\sum_{i=1}^{\mathcal{I}}\mathcal{A}_{i^2}\big) + \big(\sum_{j=1}^{\mathcal{J}}\text{P}_{j^2}\big) + \big(\sum_{k=1}^{\mathcal{K}}\text{C}_{k^2}\big)\Big] + \text{M4}\Big[\sum_{s=1}^{\mathcal{U}}\mathcal{E}_{s^2}\Big], with \sum_{i=1}^{\mathcal{I}}\mathcal{A}_i = \sum_{j=1}^{\mathcal{J}}\text{P}_j = \sum_{k=1}^{\mathcal{K}}\text{C}_k = \sum_{s=1}^{\mathcal{U}}\mathcal{E}_s = 0; \qquad \textbf{(4)}$$

where M_1, M_2, M_3, and M_4 are weights with $0<<M_1<<M_2<<M_3<<M_4$ (<< symbolizes "much less than). The ε_{ijk}s are residuals. The dependent variable h is minimized with respect to the A_i s, P_j,s, C_ks,, and εs.

In the literature, there is a consensus amongst researchers that using cohort analysis can potentially generate spurious results because age, period, and cohort are inherently confounded with each other and the result is that analysis in which behavior is explained by all variables is not possible (Baltes, 1968; Glenn, 1976). Cohort analysis seeks to explain an outcome by the exploitation of differences between cohorts as well as differences across two other temporal dimensions: "age" (time since system entry) and "period" (times when an outcome is measured)(Mason et al., 1973). The main argument is that if age, period, and cohort are treated as continuous variables, then cohort will be the difference between age and period.

In this case, it will be impossible to estimate all parameters in Equation 2, because Cohort=Period=Age is confounded (this is about the identification problem discussed above). Confounding occurs when a factor (Thadhani and Tonelli, 2006) is associated with both exposure and outcome. A classic example of confounding is the observation that coffee drinkers are at higher risk for lung cancer. In this example, cigarette smoking is a confounder, because it is associated with both the exposure (smokers are more likely to drink coffee) and the outcome (cancer).

One of the remedies to this confounding of age, period, and cohort has been for cohort analysis to be performed ignoring one of the three independent variables (Ryder,1965). Criticism of

Ryder's paper was mainly that his suggestion does not work in all cases. According to Mason et al. (1973, p.7), any analysis which omits one of the three variables can result in a spurious result finding, if age, period, and cohort have 'distinct' causal interpretations. The only conditions under which a three-way cohort analysis is possible can be represented in Equation 5:

$$Y_{ijk} = \mu + A_i + P_j + C_k + \varepsilon_{ijk}\ (i=1,,,,r;\ j=1,\ldots,s;\ k=1,\ldots r+s-1). \quad \textbf{(5)}$$

In Equation 5 the effect of the i-th age cohort is given by A_i, the effect of the j-th period by P_j, the effect of the k-th cohort by C_k, and μ is the grand mean of the dependent variable while ε_{ijk} is the random disturbance.

Numerous authors, including Rodgers (1982a; 1982b), have attempted to resolve the confounding issue associated with adopting cohort models. Mason et al. (1973) showed that the confounding may be resolved using Equation 5 if two coefficients are set equal within the three dimensions of age, period, and cohort. The equality constraints are chosen on the basis of which variables are of the least interest (Rentz et al., 1983, p.15). When equality constraints are placed on each of the three variables of age, period, and cohort, any noticeable differences can be estimated among the three unconstrained sub-variables of age, period, and cohorts, and the related three oldest sub-variable(s).

With regard to what the suitable estimation technique ought to be, the authors suggest using the constrained multiple regression (CMR) for the estimations of age, period, and cohort effects, in the following ways: To estimate the age model, equality constraints can be placed on two oldest periods, two oldest cohorts (usually the least significant ones are selected), and the oldest age class. This means then that only four of the age classes are allowed to vary in order to determine any differences between unconstrained age class sub-variables and the oldest age class sub-variable. For estimating the period model, equality constraints can be placed on the two oldest age classes, two oldest cohorts, and the earliest period. This means that only three periods can be allowed to vary in order to determine any differences between the unconstrained period sub-variables and the oldest period sub-variable. And for the cohort model, the authors suggest that it can be estimated by placing equality constraints on two oldest age classes, two oldest periods, and the oldest birth cohort, while seven cohorts can be allowed to vary in order to determine the differences between the unconstrained cohort sub-variables and the oldest birth cohort sub-variable. Before discussing tests' estimations based on U.S. consumer bankruptcy data, next, this study first presents the data sources and description of variables.

5. DATA SOURCES AND DESCRIPTION OF VARIABLES

This study has one dependent variable, which is change in percentage rates of U.S.

consumer bankruptcy filings, and three independent variables of age class, period-specific events, and birth cohort effects. The sources of the annual series data of U.S. consumer bankruptcy filings are the Institute for Financial Literacy (Linfield, 2010), American Association of Retired Persons (AARP) (Thorne et al, 2008), and Warren et al. (2000).

For the description of the age-class variable, bankrupt consumer filers are divided into 5 age classes of ten-year intervals:<24, 25-34, 35-44, 45-54, and 55+. The age-class variable captures the effects of the aging process on consumer bankruptcy filings. According to Rentz et al. (1983), in cohort studies, researchers must ensure that intervals between the age-class and periodic-event variables must correspond. In view of that, for the periodic-event intervals, this study then adopts ten-year period intervals to correspond to the ten-year age intervals. The four ten-year periods under study are 1981, 1991, 2001, and 2011. Also, for the birth-cohort variable, the birth-cohort intervals must correspond to the age-class and periodic-event intervals. The cohort intervals are divided into eight ten-year birth cohorts, representing people born from 1917 to 1987.

In the following section, this study analyzes data on the U.S. consumer bankruptcy filings for the three independent variables of age class, periodic-event, and birth cohort.

Table 1: U.S. Consumer Bankruptcy Filings (percentage of total filings)

Age	1981[a]	1991[b]	2001[b]	2011[c]
< 24	9 (D5)	9 (D6)	5 (D7)	2 (D8)
25-34	36 (D4)	36 (D5)	26 (D6)	17 (D7)
35-44	30 (D3)	30 (D4)	34 (D5)	28 (D6)
45-54	16 (D2)	16 (D3)	23 (D4)	27 (D5)
55+	9 (D1)	9 (D2)	12 (D3)	26 (D4)

D1-cohort born 1917-1926	D4-cohort born 1947-1956	D7-cohort born 1977-1986
D2-cohort born 1927-1936	D5-cohort born 1957-1966	D8-cohort born 1987-1996
D3-cohort born 1937-1946	D6-cohort born 1967-1976	

[a] *figures are Same as 1991 for there is only .09% growth in bankruptcy filings from 1980s to 1990s (Warren, 2000);*
[b]American Association of Retired Persons; [c]Institute for Financial Literacy.

Table 1 shows changes in percentage rates of U.S. bankruptcy filings by age classes and birth cohorts, for the four ten-year periods of 1981, 1991, 2001, and 2011. Reading down the period columns of Table 1, notice that bankruptcy filings begin at low percentage rates for the youngest age class (15-24); percentage rates of bankruptcy filings increase until the age class of 45-54, and, then, decrease. These changes suggest that there are cohort effects or age effects at play. Further, reading down the diagonal corner (representing cohorts) of Table 1**,** data show decreasing percentage rates of bankruptcy filings for birth cohorts over the period under study. For example, apart from the period between 1981 and 1991, notice that the rates are 9 percent in 1981 period (for the <24 age class), 36 percent in the 1991 period (for the 25-34 age class), 34 percent in the 2011 period (for the 35-44 age class), and 27 percent in 2011 period (for the 45-54 age class). These noticeable differences in percentage rates of bankruptcy filings among cohorts clearly suggest that there are age or period effects at play.

Next, reading across rows of Table 1, data show that the two oldest age classes of 45-54 and 55+ experience increases in percentage rates of bankruptcy filings. These noticeable differences in percentage rates of bankruptcy filings among age classes suggest that cohort or period effects are at play. Given that the above data analyses suggest that each of the three predictors may have some effects on percentage rates of bankruptcy filings. The question then is which has the largest effect.

6. **CONSTRAINED MULTIPLE REGRESSION ESTIMATION MODEL**

To definitively determine which of the three explanatory variables of age, period, and cohort is the most important predictor of changing U.S. consumer bankruptcy filings from 1970-2010, based on the original data in Table 1, the study now adopts the constrained multiple regression (CMR) method for estimating the three models of age class, periodic-event, and birth cohort. Ordinarily, the CMR analyses can be used to generate R-squared, coefficient estimates, and intercepts for each of the three models. The CMR estimation generates three R-squared's for each variable and the variable with the highest R-squared is considered to be the best predictor. The coefficient estimates express the effect of the i^{th} age class, j^{th} periodic event, and k^{th} birth cohort as deviation from the intercept (Rentz et al., 1983, p.15), usually at the 10 percent significant level. The interpretations for coefficient estimates of sub-variables with values below the 10 percent significant level are that there are no significant effect differences in relation to the corresponding oldest sub-variables of age class, periodic event, and birth cohort, while coefficient estimates of sub-variables with values above the 10 percent significant level indicate that there are significant effect differences in relationship to the oldest constrained sub-variables. Meanwhile, as shown in the bottom of each CMR model's column, the intercept's estimate for each model, represents the effects of all constrained sub-variables (that is, the effects of the oldest age class, periodic event, or birth cohort). Using the U.S. consumer bankruptcy filings' data in Table 1, CMR test results and interpretations are presented next, as shown in Table 2.

Interpretation of Results

A CMR analysis was adopted to estimate how the aging process, periodic economic events, and birth cohorts affect percentage rates of U.S. consumer bankruptcy filings from 1981 to 2011. In Table 2**,** the results suggest that the Age model is the best predictor, because it has the largest R-squared of 94 percent, at the 10 percent significance level. It is a standard practice in cohort studies to interpret just the results associated with the best of the three models (Rentz et al., 1983).

Table 2: Estimates for Percent Change in U.S. Consumer Bankruptcy (1981-2011)

	Age Model			**Period Model**		**Cohort Model**	
		Std.			**Std.**		**Std.**
Parameter	**Est.**[a]	**Error**		**Est**	**Error**	**Est.**	**Error**
Age							
1(15-24)	0.936[d]	.115		0.209	.124	0.277	093
2(25-34)	0.099[b]	087		0.640	.090	0.237	.068
3(35-44)	0.041[b]	.061		0.266	.058	0.074	046
4(45-54)	0.240[d]	.039		--	--	--	--
5(55+)	--[c]	--		--	--	--	--
Period							
1(1981)	--	--		--	--	--	--
2(1991)	--	--		0.480	.041	--	--
3(2001)	0.672[d]	.48		0.487	.072	0.820	.045
4(2011)	0.538[d]	.076		0.560	.105	0.951	.068
Cohort							
1(1917-1926)	--	--	--	--	--	--	--
2(1927-1936)	--	--		--	--	0.560	.057
3(1937-1946)	0.670[d]	.049		0.223	.056	0.256	.060
4(1947-1956)	0.286[d]	.070		0.074	.082	0.072	.073
5(1957-1966)	0.546[d]	.096		0.124	.110	0.119	.090
6(1967-1976)	0.914[d].120	0.328		.147	0.400	.112	
7(1977-1986)	0.535[d]	.156		0.573	.183	0.794	.140
8(1987-1996)	0.552[d]	.186		0.571	.221	0.805	.170
Intercept	0.011	.028		0.004	.004	0.095	.046
R^2	.9418	.9330		.9318	--	--	--

[a] significant at α = 10 percent significance level; [b] variables with insignificant effects; [c] variables excluded from the regression; [d] variables with significant effects

Therefore, this study now interprets the results associated with the Age Model. When the Age model is the best predictor, as it is in the case of this study, it means that cohort or period effects are the most significant. In Table 2, reading down the Age-model column, notice that only age classes of 25-34 and 35-44 have coefficient estimations of 0.099 and 0.041, below the 10 percent significant level, respectively. These results suggest that there are no significant differences in percentage rates of bankruptcy filings between both age classes in relation to the oldest age class of 55+. However, there are significant differences in percentage rates of bankruptcy filings between the age classes of 15-24 and 45-54 (with coefficient estimations of 15-24= 0.240 and 45-54= 0.936) in relation to the oldest age class of 55+. This suggests that there are cohort or period effects at play.

Next, reading down the same Age-model column, the coefficient estimates for the period sub-variables show that there are significant periodic-event effect (2001= 0.672 and 2011= 0.538) differences for 2001 and 2011 periods, relative to the two oldest periods of 1981 and 1991. These results suggest that the changes in percentage rates of U.S. consumer bankruptcy filings accelerate after 1991, and that there are cohort or age effects at play.

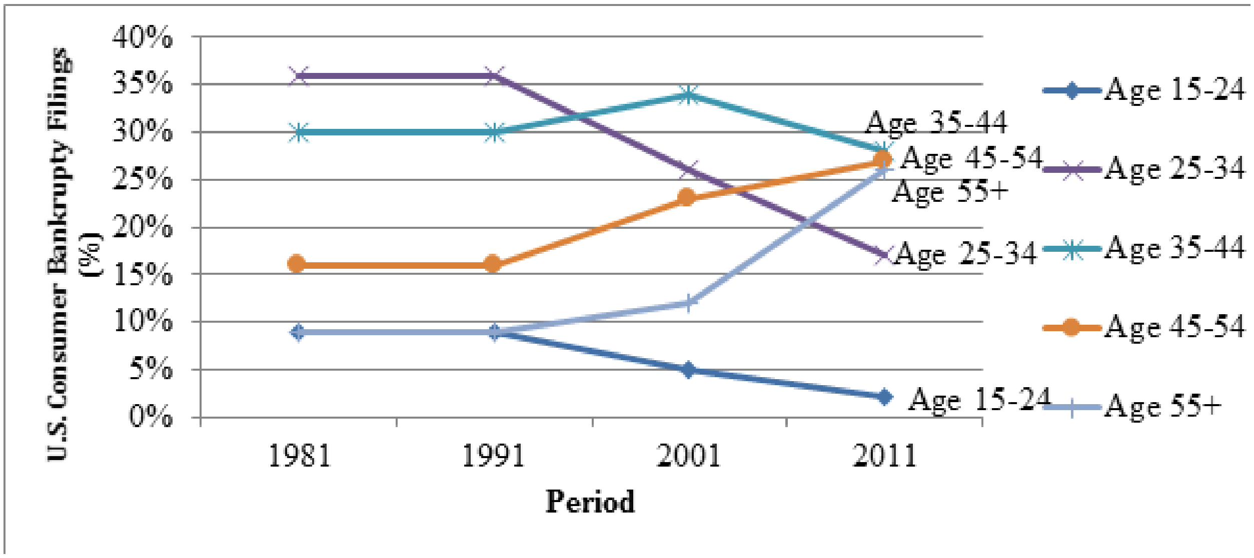
Still, reading down the Age-model column, the coefficient estimates for the cohort sub-variables show that there are significant birth-cohort-effect differences in relation to the two oldest birth cohorts (Cohorts 1 and 2). In particular, Cohort 6 (the X generation) shows the largest (0.914) birth-cohort-effect differences in relation to the two oldest cohorts, followed by, in descending order, Cohort 3 (0.670), Cohort 8 (0.552), Cohort 5 (0.546), Cohort 7 (0.535), and Cohort 4 (0.286). These differences suggest that there are significant age or period effects at play. So is the age effect or the period effect more important? To better understand which is more predominant, in Table 2, reading down the Age-model column, first, remember that in cohort studies the usual way to interpret differences among age classes of 15-24 and 45-54 is that there is a significant cohort effect or period effect. Thus, notice that members of both age classes belong to Cohorts 4 and 8. Therefore, because large members of both age classes belong to Cohort 4 and 8, then, these noticeable differences among cohort sub-variables suggest that they are caused most likely by the age effect rather than by the period effect.

But, because CMR R-squared estimations show that the Age model is the best predictor, as shown in Table 2, then the predominant predictor cannot be the age effect; it is either the cohort effect or period effect. Which of the Cohort effect and period effect is the more important? The answer is that the cohort effect is the most important predictor. This means that, under the Age model, the cohort effect is the most significant cause of differences among age sub-variables. The age effect may explain differences among birth cohorts. To summarize, CMR results, in Table 2, suggest that the cohort effect is the most important predictor, the age effect is significant, and the period effect reinforces both cohort and age effects.

Next, the study shows pictorially, using descriptive graphics (Land, 2011), that the cohort effect is indeed the most predominant predictor.

Figure 1, below, shows how consumer bankruptcy filings of the five age classes evolved over

Figure 1: U.S. Consumer Bankruptcy Filings by Age Class (1981-2011)



the periods from 1981 to 2011, based on original data in Table 1. Notice that percentage rates of bankruptcy filings are constant/steady for each of the five age classes in the 1981 and 1991 periods.

Then, from 1991 to 2001, the two age classes of 15-24 and 25-34 (mostly members of the millennial generation) experience decreases in the percentage rates of bankruptcy filings. During the same period, from 1991 to 2001, the age class of 35-44 (mostly members of the X generation) experiences increases in percentage rates of bankruptcy filings, and thereafter experiences decreases from 2001 and 2011. With regard to the two age classes of 45-54 and 55+ (mostly members of the baby boomer generation), both age classes experience increases in percentage rates of bankruptcy filings from 1991 to 2011.

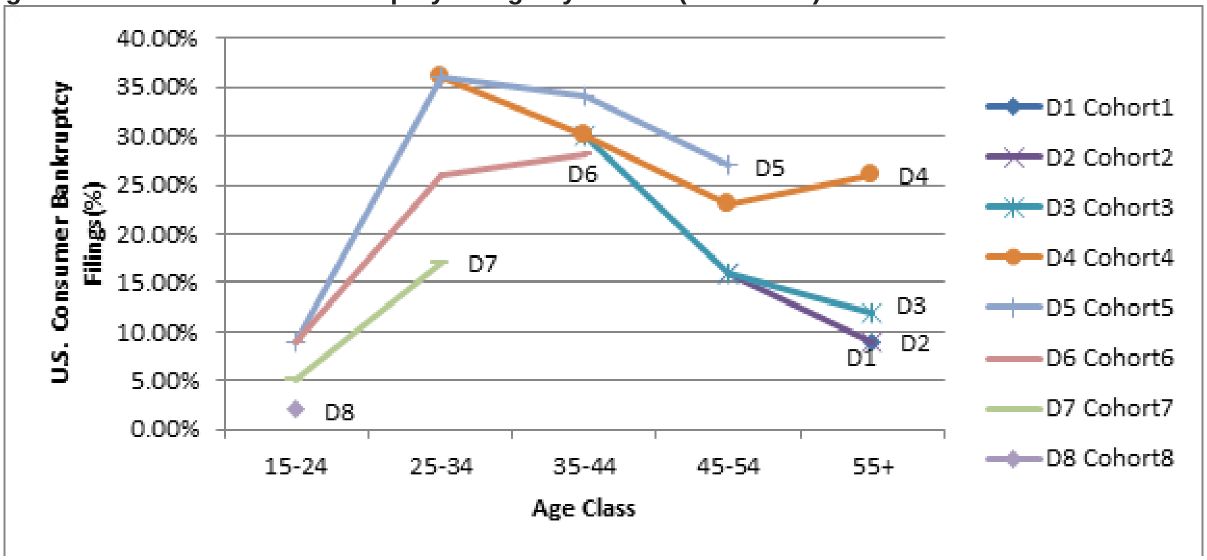
As shown elsewhere, the proper interpretation of the causes of differences among age classes is that they are caused by either the cohort effect or the period effect. Then the question becomes which of cohort effect and period effect is more predominant? The answer can be better understood by interpreting age-class lines in Figure 1. So, apart from noticeable differences in age-class lines from 1981 to 2011, notice also that the three age classes of 15-24, 25-34, and 35-44 all experience lowest percentage rates of bankruptcy filings during the 2011 period, in relation to the three previous periods.

What might explain these sudden decreases in consumer bankruptcy filings for the three age classes during the 2011 period, even though age classes of 45-54 and 55+ experience increases during the same period? The answer is the cohort effect for the following reasons. One, if it were the age effect, the best R-squared would not be the Age model; the Age model means that either cohort or period effect is at play, not the age effect. So the CMR R-squared results provide a proof that the age effect is not the most predominant predictor. Two, if it were the period effect, then all age classes would have experienced either increasing or decreasing bankruptcy filings, uniformly. Clearly, Figure 1 shows that age classes experience bankruptcy filings differently. This means that variables other than the period effect are at play, although different slopes of age-class lines at different periods suggest that the period effect reinforces the cohort effect.

By showing that age classes responded differently, Figure 1 confirms the CMR tests' results that the cohort effect is the more important predictor. If it were the period effect, then all age classes would have responded similarly across the four ten-year periods. Instead, the age classes responded to periodic-events differently as represented by different slopes of the age-class lines across the four periods.

A few studies suggest what may be the reasons for recent decreases in consumer bankruptcy filings shown in Figure 1. According to Flynn (2014), the decreases in bankruptcy filings during the 2011 period may have something to do with high administrative costs and other stringent conditions on bankrupt consumers associated with the changing legal and consumer finance environment in recent years. Another study out of Harvard University supports Flynn's finding, by showing that doubling of the costs of getting bankruptcy approval in some cases improve consumers' overall ex-post earnings or

Figure 2: U.S. Consumer Bankruptcy Filings by Cohort (1981-2011)



benefits (Dobbie, 2013). Now, the study presents graphic interpretations of U.S. bankruptcy data by birth cohort.

In Figure 2, the study uses original data in Table 1 to show how percentage rates of U.S. consumer bankruptcy filings change as each cohort advances in age. Notice, in Figure 2, that Cohorts 1 and 2 (shown as D1 and D2), the two oldest birth cohorts, experience the same percentage rates of bankruptcy filings at the age class of 55+. Cohorts 3 and 4 (shown as D3 and D4) experience increases in bankruptcy filings at the age class of 55+, in relation to Cohorts 1 and 2. Cohort 5 (shown as D5), those born from 1957 to 1966, the second batch of the baby boomer generation, experiences the largest increases in percentage rates of bankruptcy filings at the age class of 45-54. Notice also that Figure 2 shows that Cohorts 6 and 7, in relation to Cohorts 3, 4 and 5, experience decreases in percentage rates of bankruptcy filings as both cohorts reach the age class of 35-44. Meanwhile, Cohort 8, relative to when Cohorts 5, 6, and 7 are in the same age bracket, experiences the lowest percentage rates of bankruptcy filings at the age class of 15-24.

By interpretation, following the standard practice in cohort studies, Figure 2 suggests that there is either the age effect or period effect at play. The question becomes which of the age and period effect is the more predominant predictor? The answer is the age effect, for the following reasons. If it were period effect, all cohorts' lines in Figure 2 would have been either increasing or decreasing, but that is not the case. More importantly, different slopes of the cohorts' lines are indications that the period effect reinforces the predominant age effect.

In sum, the above descriptive-graphic analyses confirm earlier presented CMR estimations' results, as shown in Table 2, that the cohort effect is indeed the most predominant predictor (Figure 1), the age effect is also significant (Figure 2), and the period effect merely reinforces both age and cohort effects (Figures 1 and 2) during the period under study.

7. CONCLUDING REMARKS

This study was conducted to determine how the aging process, periodic socio-economic events, and birth cohort contributed to increases in percentage rates of U.S. consumer bankruptcy filings from 1981 to 2011. The results, based on the constrained multiple regression estimations, showed that the Age model was the best predictor. It recorded an R-squared of 94 percent as against 93.3 percent and 93.18 percent for the Period and Cohort models, respectively. The Age model being the best predictor implies that the noticeable increases in percentage rates of U.S. consumer bankruptcy filings were caused predominantly by either the cohort effect or period effect. To determine whether the cohort effect or the period effect was the more important predictor, the author also adopted graphic analysis of the data. The study found not only that the cohort effect was the most predominant predictor but also that there was a significant age effect too, and that the period effect reinforced both cohort and age effects.

Other interesting findings of the study include that the baby-boomer generation (Cohorts 4 and 5), born from 1947 to 1966, experienced the largest cohort effects, overall, and also the largest increases in percentage rates of bankruptcy filings in relation to generations preceding it. The X generation, (Cohort 6), born from 1967 to 1976, experienced the largest age and period effects. The millennial generation (Cohort 8), those consumers born from 1977 to 1996, experienced the lowest percentage rates of bankruptcy filings in relation to when preceding generations were in the same age bracket.

Yet, these findings ought to be viewed from the context of the well-acknowledged limitations of cohort analysis, which is that the methodology cannot be used to untangle all other complex variables that may potentially be affecting the changing percentage rates of U.S. consumer bankruptcy filings in the last four decades.

Still, this study makes a valid contribution to the literature in the form of providing the new evidence in support of our general understanding of the efficacy of the constrained multiple regression as pioneered by Mason et al. (1973). Another contribution of the study is that it provides empirical evidence in support of structuring certain financial products by age class and birth cohort. How realistic is it to structure financial products by age class and birth cohort? With regard to structuring financial products by age class, already, there are financial products, such as life-cycle or age-based funds that are structured based on consumers' age class, even the portfolio size of age-based funds can be taken into account in structuring financial products (Irlam, 2014).

With regard to structuring financial products by birth cohort, if financial planners already structure financial products by age class and spending habits, as it were, the author suggests that financial planners equally consider structuring of financial products by birth cohort. If adopted, this suggestion could be beneficial not only to the baby-boomer generation and others but also to the members of the millennial generation who were born at a period following the collapse of the Soviet Union, return of China to the global economy, expanding globalization, international political turmoil, and financial crisis. Therefore, this study ought to be of interest to financial planners, financial institutions, government agencies, and consumer advocacy groups.

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Football Market Efficiency and the Tout Industry: A Note

Ladd Kochman* and Randy Goodwin*

ABSTRACT

Football picks by a prominent tout service were examined for the 2014 season. Its wins-to-bets ratios for college and professional football were significantly nonrandom but not statistically profitable. While the football betting market remains efficient, football touts can nonetheless provide a useful service.

BACKGROUND

Those who can, do; those who can't, teach. When applied to football tout services, the George Bernard Shaw quip may have some truth. Football touts are paid to predict the outcomes of games for bettors. But why sell winning football picks when you can simply bet on them? The answer is that in a market generally considered to be efficient, the only regular profits result from selling rather than betting. Unlike stock picks from investment gurus that have no specific cutoff period for evaluation, football picks are judged weekly. That reality, along with the documented difficulty of outguessing the Vegas point spread, creates problems for touts. Some will acknowledge losing selections and may cite a play or call that made the difference while most will resort to a selection bias that carves out a period such as "the last three weeks" or "the last three years" when selections were more on target.

Time-specific anomalies are not uncommon in the football-betting literature but prove very little. Betting rules can generate regular profits for one or more seasons but normally fail to do so when applied to trailing years. Kochman and Gilliam (2011) placed imaginary wagers on college football teams that had lost their previous two games on the field and against the point spread during the 2004-2008 seasons and produced a wins-to-bets ratio that was significantly profitable. However, when Kochman and Badarinathi (2011) extended Kochman and Gilliam's observation period two years, profits vanished.

METHODOLOGY

To test the proposition that the football-betting market is efficient and that football touts *can't do*, we tracked the success of a respected tout service during the 2014 season. The Pointwise Information Service has been in the tout business for 46 years and supplies subscribers with a weekly newsletter in addition to phone and online conveyances. While predictions are made on all weekly college and professional games, a small fraction of games is highlighted ("key releases") and given ratings from "1" to "5" where "1" is strongest. The ratings allow us to decide whether strength-of-prediction is an important variable.

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*Kennesaw State University, Department of Economics, Finance and Quantitative Analysis

RESULTS

The small sample sizes for colleges (113) and professionals (83) precluded significantly profitable wins-to-bets ratios. However, the 61.4-percent W/B ratio for professionals was significantly nonrandom at $p < 0.05$. The colleges' mark of 54.9 percent was significantly nonrandom at $p < 0.30$. No relationship between ratings and W/B ratios was observed in either Table 1 or Table 2.

CONCLUSIONS

So do touts matter? Or, more fundamentally, is the football betting market efficient? The answers would seem to be *yes* and *maybe*, respectively. For bettors simply wanting action, wins-to-bets ratios of 61.4 percent and 54.9 percent suggest that football betting can be a costless recreational pursuit[1] with help from the tout industry. For bettors motivated by financial gain, the value of touts is less clear. Larger sample sizes may reveal that the tout industry boasts some superior analysts that can challenge the efficiency of a competitive market.

Table 1

Rated picks in college football (2014)

Rating	*Wins/Bets*	*W/B%*
1	16/29	55.2%
2	5/12	41.7%
3	12/15	80.0%
4	16/27	59.3%
5	13/30	43.3%
Overall	Wins/Bets	W/B%
1-5	62/113	54.9%

Table 2

Rated picks in professional football (2014)

Rating	*Wins/Bets*	*W/B%*
1	0/ 0	00.0%
2	0/ 0	00.0%
3	11/17	64.7%
4	21/35	60.0%
5	19/31	61.3%
Overall	*Wins/Bets*	*W/B%*
1-5	51/83	61.4%

ENDNOTE

1. Absent the $95 subscription price of the weekly newsletters..

REFERENCES

Kochman, L., and R. Badarinathi. "The Gambler's Fallacy: A Test of Football Betting Market Efficiency." *Virginia Economic Journal,* Vol. 16, 2011.

Kochman, L., and K. Gilliam. "Football Market Efficiency and the Gambler's Fallacy." *Journal of Business and Economic Perspectives.* Spring/Summer 2011.

Ma, J. "The Trouble with the Tout Industry." ESPN, October 30, 2014.

________________________. Pointwise Information Service. Syracuse, NY. 2014.

REFEREES

1. Tavis Barr
2. Paul Bauer
3. James Booker
4. Joseph Cheng
5. Dal Didia
6. Niev Duffy
7. Mark Gius
8. Elia Kacapy (2)
9. William O'Dea
10. Dona Siregar
11. Philip Sirianni
12. Jeffrey Wagner

The New York State Economics Association

66th Annual Conference
Farmingdale State College
October 4th and 5th, 2013

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Schedule of Events

Friday, October 4, 2013

6:00pm	Reception, Townplace Suites
6:30pm	Welcome – Dr. Hubert Keen, President, Farmingdale State College

Saturday October 5, 2013

7:30am-8:00am	Registration and Continental Breakfast
8:00am-8:15am	Welcome
8:15am-9:35am	Concurrent Sessions: Group A
9:35am-9:50am	Morning Break
9:50am-11:10am	Concurrent Sessions: Group B
11:25am-12:40pm	Luncheon and Keynote Address Dr. David Harper
12:50pm-2:10pm	Concurrent Sessions: Group C
2:10pm-2:25pm	Afternoon Break
2:25pm-3:45pm	Concurrent Sessions: Group D
4:00pm-5:00pm	Business Meeting (All Are Welcome)

Friday, October 4, 2013

6:00-9:00pm Reception, TownePlace Suites by Marriot

6:30pm Welcome

Dr. Hubert Keen, President, Farmingdale State College

Saturday, October 5, 2013

7:30-8:00AM REGISTRATION AND CONTINENTAL BREAKFAST

Farmingdale State College Campus, Nathan Hale Hall

8:00-8:15AM WELCOME

Dr. Richard Vogel, Ph.D., Dean, School of Business, Farmingdale State College

8:15-9:35AM CONCURRENT SESSIONS A

Session A10 **Economics of Collegiate Sports (Roundtable)**
Nathan Hale Hall 126
Chair: Glenn Gerstner (St. John's University), gerstneg@stjohns.edu

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Title: Roundtable on Sports
Author: Glenn Gerstner (St. John's University), gerstneg@stjohns.edu

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Title: Sports Economics Roundtable
Author: Darius J. Conger (Ithaca College), dconger@htva.net

Title: Sports Economics Roundtable
Author: Richard Vogel (Farmingdale State College), Richard.Vogel@farmingdale.edu

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Session A11 **Health & Education 1**
Nathan Hale Hall 137
Chair: Ambrose Jusu (Farmingdale State College), jusua@farmingdale.edu

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Title: Macroeconomic Policies and Their Impact On Health In Sierra Leone: An Analysis of the Prevalence of Malaria, Malnutrition And Maternal Mortality
Author: Ambrose Jusu (Farmingdale State College), jusua@farmingdale.edu
Discussant: Roberta Schroder (Nassau Community College), Roberta.schroder@ncc.edu

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Title: Demand for Voluntary HIV Testing
Authors: Kpoti Kitissou (Binghamton University), kkitiss1@binghamton.edu
Bong Joon Yoon (Binghamton University), yoon@binghamton.edu
Discussant: Michal Padway (The New School University), padwm338@newschool.edu

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Title: The Role of Socio-Economic Factors in Determining Contraceptive Choice in Developing Countries
Author: Ran Meng (Albany College of Pharmacy and Health Sciences), ran.meng@acphs.edu
John M. Polimeni (Albany College of Pharmacy and Health Sciences), john.polimeni@acphs.edu
Discussant: Kpoti Kitissou (Binghamton University), kkitiss1@binghamton.edu

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Session A12

Macroeconomy & Financial Markets 1
Nathan Hale Hall 224
Chair: O. David Gulley (Bentley University), dgulley@bentley.edu

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Title: Revisiting the U.S. Corporate Income Tax: Philosophical and Structural Problems
Author: Anthony Pappas (St. John's University), anthonypappas1988@gmail.com
Discussant: Damir Cosic (CUNY Graduate Center), dcosic@gc.cuny.edu

---

Title: Does Crowd Out Offset The Stimulus Effect of Government Deficits? A Large Scale Econometric Study **Author**:
John J. Heim (SUNY Albany), jheim@albany.edu
Discussant: O. David Gulley (Bentley University), dgulley@bentley.edu

---

Title: Anticipated Consumption Tax Reforms
Author: Quian Li (SUNY Stony Brook), phoenixquianli1985@gmail.com
Discussant: Anthony Pappas (St. John's University), anthonypappas1988@gmail.com

---

Title: The Effect of Firm Size on Income and Wealth Inequality
Author: Damir Cosic (CUNY Graduate Center), dcosic@gc.cuny.edu
Discussant: Quian Li (SUNY Stony Brook), phoenixquianli1985@gmail.com

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Session A13

International Trade & Finance 1
Nathan Hale Hall 226
Chair: Dongyun Lin (Farmingdale State College), linna334@gmail.com

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Title: Empirical Analysis of Determinants of Corruption in Nigeria
Author: L. Chukwudi Ikwueze (Farmingdale State College), chuikwueze@aol.com
Discussant: Wisdom Akpalu (Farmingdale State College), akpaluw@farmingdale.edu

---

Title: The Impact of Remittances of Exchange Rate Volatility in Dollarized Economies
Author: Helena Glebocki Keefe (Fordham University), hglebocki@fordham.edu
Discussant: Abeba Mussa (Farmingdale State College), mussaa@farmingdale.edu

---

Title: Growth Potential of Intra-African Trade
Author: L. Chukwudi Ikwueze (Farmingdale State College), chuikwueze@aol.com
Discussant: Dongyun Lin (Farmingdale State College), linna334@gmail.com

---

Title: Bilateral Trade Between Quebec and New York State: Granger Causality Analysis
Authors: Edouard Mafoua (SUNY Canton), mafouae@canton.edu
Pascal Ndinga (University of Quebec at Montreal), ndinga.pascal@uqam.ca
Discussant: Kent Klitgaard (Wells College), kentk@wells.edu

Session A14 **Economic Development 1**
Nathan Hale Hall 231
Chair: Prabal De (The City College of New York), pde@ccny.cuny.edu

---

Title: Obstacles to Education in Underdeveloped Countries: The Case of a Tanzanian Town
Author: Yu-li Ko (Rensselaer Polytechnic Institute), koy2@rpi.edu
Yunsuk Ko (Good Neighbors Tanzania), atuan.ko@gmail.com
Discussant: Hsinrong Wei (Bronx Community College), hsinrong.wei@bcc.cuny.edu
---
Title: Household Shocks and Transition into Marriage: Evidence from Rural Ethiopia
Author: Boyd Tembo (CUNY Hunter College), btembo@hunter.cuny.edu
Discussant: Yu-li Ko (Rensselaer Polytechnic Institute), koy2@rpi.edu
---
Title: Does FDI Improve Financial Deepening of Host Country Stock Markets? Evidence from Sectoral FDI
Author: Nadia Doytch (Brooklyn College), ndoytch@brooklyn.cuny.edu
Discussant: Sean P. MacDonald (New York City College of Technology)

Title: Relationship between Financial Intermediation and the Capital Account in Egypt
Author: Ossama Elhadary (City University of New York), oelhadary@gc.cuny.edu
Discussant: Prabal De (The City College of New York), pde@ccny.cuny.edu

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Session A15

Undergraduate Student Paper Competition 1
Lupton Hall T101
Chair: Manimoy Paul (Siena College), mpaul@siena.edu

Examining the Influence of Microfinance on Household Conditions in Hyderabad, India

Tara Fleming (SUNY Oswego), tflemin3@oswego.edu

Robert Culp (Dalton State College), rculp@daltonstate.edu

The Effects of the 2007-2009 Financial Crisis on the Cointegration Relationship Between Stock Markets

Julia Fremante (SUNY Oneonta), fremjr72@suny.oneonta.edu

Dolore Bushati (Nassau Community College), d_burimi@yahoo.com

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Short Term US Natural Gas Markets: Forecast Versus Futures at the Henry Hub

Barney Chen (CUNY City College of New York), pxpx41385@gmail.com

David Ring (SUNY Oneonta), david.ring@oneonta.edu

Layoff Announcement Effects for the Stock Price of Financial Institutions

Mark Russo (St. John’s University), mark.russo09@stjohns.edu

William P. ODea (SUNY Oneonta), odeawp@oneonta.edu

The State-Led Exploitation of Labor Migration from Bangladesh

Wahid Kahn (Ithaca College)
Discussant: Michael McAvoy (SUNY Oneonta), Michael.mcavoy@oneonta.edu
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9:35-9:50AM MORNING BREAK

9:50-11:10AM CONCURRENT SESSIONS B

Session B20 **Finance & Policy 1**
Nathan Hale Hall 126
Chair: Ermese Ivan (St. John's University), ivane@stjohns.edu
----
Title: Cohort Analysis of the U.S. Consumer Bankruptcy
Author: L. Chukwudi Ikwueze (Farmingdale State College), chuikwueze@aol.com
Discussant: Ermese Ivan (St. John's University), ivane@stjohns.edu
---
Title: Financing Sport in Europe: An International and Comparative Perspective
Author: Ermese Ivan (St. John's University), ivane@stjohns.edu
Discussant: Fangxia Lin (New York City College of Technology), fxlin@citytech.cuny.edu
---
Title: Literature vs. Reality: Bank Valuation Methods Used By Equity Analysts
Author: K. Matthew Wong (St. John's University), wongk@stjohns.edu
Jose Luis Valasc (International School of Management, Paris, France)
Discussant: L. Chukwudi Ikwueze (Farmingdale State College), chuikwueze@aol.com
---

Session B21

Economic Development 2
Nathan Hale Hall 137
Chair: Joshua Greenstein (The New School for Social Research), greej586@newschool.edu
----
Title: A (New) Theory of Urban Informality
Author: Prabal De (The City College of New York), pde@ccny.cuny.edu
Debipriya Chatterjee (University of Wisconsin – Milwaukee), chatterj@uvm.edu
Discussant: Joshua Greenstein (The New School for Social Research), greej586@newschool.edu
---
Title: Growth and Distribution Across Multiple Dimensions in Middle Income Countries
Author: Joshua Greenstein (The New School for Social Research), greej586@newschool.edu
Discussant: Prabal De (The City College of New York), pde@ccny.cuny.edu
---
Title: Does Financial Liberalization Impact Economic Growth: Case of Asian Economies
Author: Hsinrong Wei (Bronx Community College, CUNY), hsinrong.wei@bcc.cuny.edu
Discussant: Dongyun Lin (Farmingdale State College), linna334@gmail.com
---

Session B22 **Health & Education 2**
Nathan Hale Hall 224
Chair: Ran Meng (Albany College of Pharmacy and Health Sciences), ran.meng@acphs.edu

---

Title: The Role of Spouses Heath Conditions on the Decision of Nursing Home Entry of the Elderly Couples in the United States
Author: Jinyoung Eom (SUNY Stony Brook), eomjiy@gmail.com
Discussant: Ritu T. Shah (Albany College of Pharmacy and Health Sciences
---
Title: Cost of Cancer Treatment Differences for U.S. Veterans and Non-Veterans
Author: Ritu T. Shah (Albany College of Pharmacy and Health Sciences), ritu.shah@acphs.edu
Wendy Parker (Albany College of Pharmacy & Health Sciences), wendy.parker@acphs.edu
John Polimeni (Albany College of Pharmacy & Health Sciences), john.polimeni@acphs.edu
Discussant: Kpoti Kitssou (Binghamton University), kkitiss1@binghamton.edu

Title: Differences in the Utilization of Preventive Services for U.S. Veterans and Non-Veterans
Author: Ritu T. Shah (Albany College of Pharmacy and Health Sciences), ritu.shah@acphs.edu Wendy Parker (Albany College of Pharmacy and Health Sciences), wendy.parker@acphs.edu John Polimeni (Albany College of Pharmacy and Health Sciences), john.polimeni@acphs.edu
Discussant: Yan Song (CUNY Graduate Center), songyan0708@gmail.com
---
Title: The Effect of Interaction Between Time Preference and Price on Pregnant Women Smoking Behavior
Author: Yan Song (CUNY Graduate Center), songyan0708@gmail.com
Discussant: Ritu T. Shah (Albany College of Pharmacy and Health Sciences), ritu.shah@acphs.edu
---

Session B23 **Labor 1**
Nathan Hale Hall 226
Chair: Xu Zhang, Farmingdale State College, zhangx@farmingdale.edu

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Title: Unemployment, a Catalyst for Changes to the Military Enlistment Population
Author: Clifford Goss (Fordham University), goss@fordham.edu
Discussant: Yoo Bin Kim (SUNY Stony Brook), yoo.b.kim@stonybrook.edu
---
Title: Gender and Job Location Choices: Evidence from Rural Migrants in China
Author: Xu Zhang (Farmingdale State College), zhangx@farmingdale.edu
Discussant: Abhinav Anand (SUNY Stony Brook), abbinav.anand@stonybrook.edu
---
Title: Labor Supply of Immigrants near Retirement Age and Social Welfare Program Eligibilities
Author: Yi Zhang (SUNY Stony Brook), yi.zhang.2@stonybrook.edu
Discussant: Xu Zhang (Farmingdale State College), zhangx@farmingdale.edu
---
Title: Quotas Versus Handicaps: A Game Theoretic Analysis of Affirmative Action Policies in India
Author: Abbinav Anand (SUNY Stony Brook), abhinav.anand@stonybrook.edu
Discussant: Hyeon Park (Manhattan Colelge), hyeon.park@manhattan.edu
---

Session B24 **Macroeconomy & Financial Markets 2**
Nathan Hale Hall 231
Chair: John J. Heim (SUNY Albany), jheim@albany.edu

Title: Corporate Liquidity, Default Risk and the US Great Depression
Author: Lunan Jiang (SUNY Stony Brook), lunan.jiang@stonybrook.edu
Discussant: Julie K. Smith (Lafayette College), smithjk@lafayette.edu
---
Title: Loan Flows and Monetary Policy
Author: Richard Robinson (SUNY Fredonia), Richard.robinson@fredonia.edu
Marwan ElNasser (SUNY Fredonia), marwin.elnasser@fredonia.edu
MaryAnn Robinson (SUNY Fredonia), marobinson@fredonia.edu
Discussant: Yan Liu (SUNY Stony Brook), yan.liu@stonybrook.edu
---
Title: Information Production, Bank Runs, and Disintermediation
Author: Yan Liu (SUNY Stony Brook), yan.liu@stonybrook.edu
Discussant: John J. Heim (SUNY Albany), jheim@albany.edu

Title: The Term Structure of State Bond Interest Rates
Author: Kevin Foster (The City College of New York), aespinosa@ccny.cuny.edu
Adriana Espinosa (The City College of New York), john.schmitz@gmail.com
John Schmitz (The City College of New York), john.schmitz@gmail.com
Discussant: Yan Liu (SUNY Stony Brook), yan.liu@stonybrook.edu
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Session B25

Undergraduate Student Paper Competition 2
Lupton Hall T101
Chair: Manimoy Paul (Siena College), mpaul@siena.edu

Title: A Savage By Any Other Name: Anthropological Inaccuracies in the Writings of Adam Smith

Author: Dawn Rivers (Hartwick College), riversd@hartwick.edu

Discussant: Arindam Mandal (Siena College), amandal@siena.edu

---

Title: Microfinance in South Africa: Gender and Race Responses to Different Marketing Tactics

Author: Eric Benvenuti (Hamilton College), eric@cipequity.com

Discussant: Manimoy Paul (Siena College), mpaul@siena.edu

Title: An Analysis of Intergenerational Income Mobility

Author: Thomas J. Hedin (Carthage College), thedin1@carthage.edu

Discussant: Nadia Doytch (Brooklyn College), ndoytch@brooklyn.cuny.edu

---

Title: Capital Structure and Liability in the Tobacco Industry

Author: Victor Angeline IV (Hartwick College), angelinev@hartwick.edu
Kristi R. Jones (Hartwick College), jonesk@hartwick.edu
Thomas Devaney (Hartwick College), devaneyt@hartwick.edu
Discussant: Joo-Kyung Sung (Ramapo College), jsung@ramapo.edu
---

Title: Trends of Economic Development in the Post-Crisis Era. Creating a Sustainable Future for Young People
Author: Jasmina Tacheva (Canisius College), j.tacheva@gmail.com
Discussant: David Ring (SUNY Oneonta), david.ring@oneonta.edu
---

Session B26 **Sports Economics**
Nathan Hale Hall 234
Chair: Darius J. Conger (Ithaca College), dconger@htva.net

Title: Testing Market Efficiency in the English Premier League
Author: Seung Hyun Kuk (Emory University), skuk@emory.edu
Wooyoung Ryan Choi (Emory University), wchoi37@emory.edu
Discussant: Michael McAvoy (SUNY Oneonta), Michael.mcavoy@oneonta.edu
---
Title: Pay, Performance, and the Reserve Clause in Major League Baseball: The American Associations Cincinnati Club during the 1880s
Author: Michael McAvoy (SUNY Oneonta), Michael.mcavoy@oneonta.edu
Discussant: Darius J. Conger (Ithaca College), dconger@htva.net
---
Title: Death (and Resurrection?) of an Arena
Author: Ira Stolzenberg (Farmingdale State College), stolzei@farmingdale.edu
Discussant: Eric Doviak (York College), eric@doviak.net

Title: A Simple Model of Baseball Integration
Author: Timothy Kearney (Misericordia University), tkearney@misericordia.edu
David Gargone (Misericordia University), dgargone@misericordia.edu
Discussant: Ira Stolzenberg (Farmingdale State College), stolzei@farmingdale.edu

11:25-12:40PM LUNCHEON AND KEYNOTE ADDRESS

"Welcome to Legoland: Innovation and the Emergent Complexity of Property Rights" Dr. David A. Harper
New York University

David Harper is a specialist in entrepreneurship and innovation. He has worked in both research and public policy settings. He was formerly a senior adviser on regulation and competition policy at the New Zealand Treasury, and is currently in the Economics Department at NYU, where he is Director of the master's program in economics and Co-Director of the Foundations of the Market Economy Program.

12:50-2:10PM CONCURRENT SESSIONS C

Session C30 **Environmental Economics 1**
Nathan Hale Hall 126
Chair: Worku T. Bitew (Farmingdale State College), biteww@ farmingdale.edu

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Title: Bioeconomic Model of Externalities and Foreign Capital in Aquaculture Production in Africa
Author: Worku T. Bitew (Farmingdale State College), biteww@farmingdale.edu
Wisdom Akpalu (Farmingdale State College), akpaluw@farmingdale.edu
Discussant: Jeffrey Wagner (Rochester Institute of Technology), Jeffrey.wagner@rit.edu
---
Title: Too Many Cliffs
Author: Kent Klitgaard (Wells College), kentk@wells.edu
Discussant: Worku T. Bitew (Farmingdale State College), biteww@farmingdale.edu
---
Title: Farmer Participation in Interlinked Transactions in Rural Markets: The Case of Purchase for Progress (P4P) in Ghana
Author: Wisdom Akpalu (Farmingdale State College), akpaluw@farmingdale.edu
Discussant: Kevin Foster (The City College of New York), kfoster@ccny.cuny.edu
---

Session C31 **The Great Recession**
Nathan Hale Hall 137
Chair: Arindam Mandal (Siena College), amandal@siena.edu

Title: The Great Recession and the Gender Based Discrimination in the Labor Market: Evidence from New York State Author: Arindam Mandal (Siena College), amandal@siena.edu
Discussant: Lunan Jiang (SUNY Stony Brook), lunan.jiang@stonybrook.edu
---
Title: An Evaluation of the Effectiveness of Mortgage Loan Modification Programs: A Comparative Analysis of Eight Metropolitan Areas: 2009-2012
Author: Sean P. MacDonald (New York City College of Technology), smacdonald@citytech.cuny.edu
Discussant: Thomas Conoscenti (Thomas Conoscenti and Associates), thomas.conoscenti@gmail.com
---
Title: The Panic of 2008 and a History of Modern Finance
Author: William T. Ganley (Buffalo State College), ganleywt@buffalostate.edu
Discussant: Lunan Jiang (SUNY Stony Brook), lunan.jiang@stonybrook.edu
---
Title: A Mortgage Product that Improves Labor Mobility while Reducing Systemic Risk
Author: Robert Culp (Dalton State College), rculp@daltonstate.edu

Discussant: Ermese Ivan (St. John's University), ivane@stjohns.edu
---

Session C32 **The College Fed Challenge: How to Prepare a Team (Roundtable) Nathan Hale Hall 224**
Chair: Joo-Kyung Sung (Ramapo College), jsung@ramapo.edu
Discussant: Alexandre Olbrecht (Ramapo College), aolbrech@ramapo.edu

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Title: Macro Quest Project – Generating interest and Building a Fed
Challenge Team Author: Della L. Sue (Marist College), della.lee.sue@marist.edu
---
Title: Using an Academic Competition – Based Course to Foster Student Learning
Author: O. David Gulley (Bentley University), dgulley@bentley.edu
Aaron L. Jackson (Bentley University), ajackson@bentley.edu

Title: The College Fed Challenge: An Innovation in Cooperative Learning
Author: Julie K. Smith (Lafayette College), smithjk@lafayette.edu
Cynthia Bansak (St. Lawrence University), cbansak@stlawu.edu

Session C33 **Labor 2**
Nathan Hale Hall 226
Chair: Wade Thomas (SUNY Oneonta), wade.thomas@oneonta.edu

Title: Determinants of Physician Distribution in the United States
Author: Dane Weinert (Emory University),daweineemory.edu
Discussant: Jieruo Liu (SUNY Stony Brook), jieliu@ic.sunysub.edu
---
Title: Estimating the Impact of Taxation and Transfer on Search Dynamics
Author: Yoo Bin Kim (SUNY Stony Brook), yoo.b.kim@stonybrook.edu
Discussant: Wade Thomas (SUNY Oneonta), wade.thomas@oneonta.edu
---
Title: Late-Career Job Displacement and Retirement Decisions Among Older Americans
Author: Jieruo Liu (SUNY Stony Brook), jieliu@ic.sunysb.edu
Discussant: Joseph Mauro (Fordham University), jmauro6@fordham.edu
---
Title: Understanding Inactive and Out-of-School Youth in Eastern and Central Asia
Author: Joseph Mauro (Fordham University), jmauro6@fordham.edu
Sophie Mitra (Fordham University), mitra@fordham.edu
Discussant: David Ring (SUNY Oneonta), david.ring@oneonta.edu
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Session C34 **International Trade & Finance 2**
Nathan Hale Hall 231
Chair: Dongyun Lin (Farmingdale State College), linna334@gmail.com

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Title: Linking the Concept of Market Internality to the Non-Oil Sector in Nigeria
Author: L. Chukwudi Ikwueze (Farmingdale State College), chuikwueze@aol.com
Discussant: K. Matthew Wong (St. John's University), wongk@stjohns.edu

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Title: Asset Accumulation Behavior of Immigrants and Natives
Author: Abeba Mussa (Farmingdale State College), mussaa@farmingdale.edu
Discussant: Dongyun Lin (Farmingdale State College), linna334@gmail.com

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Session C35 **Health & Education 3**

Nathan Hale Hall 234

Chair: Olga Guska (Hunter College, CUNY), o.corpan@gmail.com

Title: The Effect of Employment Status and Business Cycles on Time Use

Author: Olga Guska (Hunter College), o.corpan@gmail.com

Discussant: Kpoti Kitissou (Binghamton University), kkitiss1@binghamton.edu

---

Title: A Systems Dynamics Approach to Cancer Development From Exposure to Phthalates in Personal Care Products

Author: Ran Meng (Albany College of Pharmacy and Health Sciences), ran.meng@acphs.edu
John M. Polimeni (Albany College of Pharmacy and Health Sciences), john.polimeni@acphs.edu

Discussant: Jinyoung Eom (SUNY Stony Brook), eomjiy@gmail.com

---

Title: Income Disparity and Health Deprivation: Cross-Country and Time-Series Analysis

Author: Michal Padway (The New School University), padwm338@newschool.edu

Discussant: Ran Meng (Albany College of Pharmacy and Health Sciences), ran.meng@acphs.edu

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Title: The Effects of Increases in Cigarette Prices on Cigarette Consumption for Smokers after MSA

Author: Zhen Ma

Discussant: Olga Guska (Hunter College, CUNY), o.corpan@gmail.com

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Session C36 **Economics Education 1**

Lupton Hall T101

Chair: Eric Doviak (York College), eric@doviak.net

Title: Are too Many Students Going to College?

Author: Veronika Dolar (LIU Post), veronica.dolar@liu.edu

Sebastien Buttet (LIU Post), seba.buttet@gmail.com

Discussant: Roberta Schroder (Nassau Community College), Roberta.schroder@ncc.edu

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Title: Debian for Android. Debian for Metrics. Debian for the Classroom

Author: Eric Doviak (York College), eric@doviak.net

Sean MacDonald (New York City College of Technology), smacdonald@citytech.cuny.edu

Discussant: Seung Hyun Kuk (Emory University), skuk@emory.edu

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Title: Effect of Texting During Class on Undergraduate Business Students' Academic Performance

Author: Manimoy Paul (Siena College), mpaul@siena.edu

Discussant: Eric Doviak (York College), eric@doviak.net

Title: Teaching the Evolution of U.S. Monetary Policy during the Recent Economic Crisis

Author: Marwin El Nasser (SUNY Fredonia), marwin.elnasser@fredonia.edu

Richard Robinson (SUNY Fredonia), Richard.robinson@fredonia.edu

Discussant: Veronika Dolar (LIU Post), veronica.dolar@liu.edu

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2:10-2:25PM AFTERNOON BREAK

2:25-3:45PM CONCURRENT SESSIONS D

Session D40 Macroeconomy & Financial Markets 3

Nathan Hale Hall 126

Chair: Richard Robinson (SUNY Fredonia), Richard.robinson@fredonia.edu

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Title: A Thirty Equation Econometric Model of the U.S.

Author: John J. Heim (SUNY Albany), jheim@albany.edu

Discussant: Lin Zhang (SUNY Stony Brook), zhanglinbaylor@gmail.com

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Title: Poverty and the Macroeconomy: Evidence from Linear Regression Across Poverty Measures

Author: Liliana Martinez (Rensselaer Polytechnic Institute), martil@rpi.edu

Adam Sales (Unviersity of Michign), acsales@umich.edu

Discussant: Richard Robinson (SUNY Fredonia), Richard.robinson@fredonia.edu

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Title: The Impact of Responsiveness of Monetary Policy on Housing Market – An Estimated DSGE Model

Author: Lin Zhang (SUNY Stony Brook), zhanglinbaylor@gmail.com

Discussant: Sibel Korkmaz (PhD Student, CUNY Graduate Center), skorkmaz@gc.cuny.edu

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Title: Predictability of Bond Risk Premia and Market Price Author:

Sibel Korkmaz (PhD Student, CUNY Graduate Center)

Discussant: Lin Zhang (SUNY Stony Brook), zhanglinbaylor@gmail.com

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Session D41 Environmental Economics 2

Nathan Hale Hall 137

Chair: Jeffrey Wagner (Rochester Institute of Technology), Jeffrey.wagner@rit.edu

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Title: Put Your Money Where Your Carbon Is: Estimating the Willingness-to-Pay for Carbon Emissions of Fee-Paying Commuters

Author: Zachary Van Earden (SUNY Oneonta), vanezj37@oneonta.edu

Phillip Sirianni (SUNY Oneonta), Philip.sirianni@oneonta.edu

William ODea (SUNY Oneonta), William.odea@oneonta.edu

Discussant: O. David Gulley (Bentley University), dgulley@bentley.edu

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Title: Disaster Policy and the New York Metropolitan Area

Author: Richard Vogel (Farmingdale State College), Richard.vogel@farmingdale.edu

Discussant: Jeffrey Wagner (Rochester Institute of Technology), Jeffrey.wagner@rit.edu

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Title: Promoting Nutritious Food Consumption and Sustainability in Low-Income Food Desert Urban Neighborhoods

Author: Jeffrey Wagner (Rochester Institute of Technology), Jeffrey.wagner@rit.edu

Cam Hebda (Rochester Institute of Technology), camhebda@gmail.com

Discussant: Wisdom Akpalu (Farmingdale State College), akpaluw@farmingdale.edu

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Session D42 Finance & Policy 2

Nathan Hale Hall 224

Chair: Aiwu Zhao (Skidmore College), azhao@skidmore.edu

Title: Extreme Dependence Across East Asian Financial Markets: Evidence in Equity and Currency Markets

Author: Fangxia Lin (New York City College of Technology), fxlin@citytech.cuny.edu

Discussant: K. Matthew Wong (St. John’s University), wongk@stjohns.edu

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Title: The Value of Institutional Privilege and Competitve Capacity in Vietnamese Stock Markets

Author: Aiwu Zhao (Skidmore College), azhao@skidmore.edu Xue Xue (Skidmore College),

Discussant: Anthony Pappas (St. John's University), anthonypappas1988@gmail.com

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Title: Exchange Rate and China's Economic Growth

Author: Dongyun Lin (Farmingdale State College), linna334@gmail.com

Discussant: Aiwu Zhao (Skidmore College), azhao@skidmore.edu

Session D43 New York State Economy

Nathan Hale Hall 226

Chair: Paul Bauer (SUNY Oneonta), paul.bauer@oneonta.edu

Title: Residential Property Values in Oneonta: Are Student Rentals a Negative or Positive Externality?

Author: Paul Bauer (SUNY Oneonta), paul.bauer@oneonta.edu

Discussant: Edouard Mafoua (SUNY Canton), mafouae@canton.edu

Title: Descriptive Analysis of High-Tech Employment in the Buffalo-Niagara Falls, New York Metropolitan Statistical Area: 1970-2010

Author: Craig Rogers (Canisius College), rogersc@canisius.edu

Discussant: Paul Bauer (SUNy Oneonta), paul.bauer@oneonta.edu

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Title: New York Metropolitan Area Effective Real Property Tax Rates, 1997-2009

Author: Thomas Conoscenti (Thomas Conoscenti and Associates), Thomas.conoscenti@gmail.com
David Listokin (Rutgers University),

Discussant: Jieruo Liu (SUNY Stony Brook), jieliu@ic.sunysb.edu

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Title: Economies of Scale and Scope in Increasingly Competitive New York Local Telecommunications Markets

Author: Richard E. Schuler, Jr. (New York State Department of Public Service), Richard.schuler@dps.ny.gov

Discussant: Craig Rogers (Canisius College), rogersc@canisius.edu

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Session D44 Efficiency & Utility in Specialized Markets

Nathan Hale 231

Chair: Michael McAvoy (SUNY Oneonta), micahel.mcavoy@oneonta.edu

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Title: The Impact of Social Referrals on Consumer Conversion

Author: Hilary Lin (Iona College), hlin@iona.edu

Discussant: Hyeon Park (Manhattan College), hyeon.park@manhattan.edu

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Title: Why are Consumer Tastes and Expert Judgments Different: A Case Study of the Movie Industry

Author: Hilary Lin (Iona College), hlin@iona.edu

Discussant: William T. Ganley (Buffalo State College), ganleywt@buffalostate.edu

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Title: First Price Auction with Three Bidders Affected By Information

Author: Hyeon Park (Manhattan College), hyeon.park@manhattan.edu

Discussant: William C. Kolberg (Ithaca College), kolberg@ithaca.edu

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Title: Dancing with The Bees: Follow-the-Leader Market Dynamics with Robot Firms

Author: William C. Kolberg (Ithaca College), kolberg@ithaca.edu

Discussant: Hilary Lin (Temple University), Hilary.lin@temple.edu

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Session D45 Economics Education 2
Nathan Hale Hall 234
Chair: William P. O'Dean (SUNY Oneonta), odeawp@oneonta.edu

Title: What Were They Thinking: Can Student Responses to Teaching Evaluation Instruments Reveal the Qualities of an Effective Instructor?

Author: William P. ODea (SUNY Oneonta), odeawp@oneonta.edu

Discussant: James Booker (Siena College), jbooker@siena.edu

Title: Do Exam Policies Matter In Colleges?

Author: L. Chukwudi Ikwueze (Farmingdale State College), chuikwueze@aol.com

Discussant: Della L. Sue (Marist College), della.lee.sue@marist.edu

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Title: Improving Economies and Financial Literacy and Education: An Overview from a Teacher's Perspective

Author: Robert Schroder (Nassau Community College), roberta.schroder@ncc.edu
Dolore Bushati (Nassau Community College), dolore.bushati@ncc.edu

Discussant: Margaret Morrison (SUNY Oneonta), Margaret.morrison@oneonta.edu

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4:00-5:00PM BUSINESS MEETING (ALL ARE WELCOME)

NEW YORK ECONOMICS REVIEW

The New York Economic Review is an annual journal, published in the Fall. The Review publishes theoretical and empirical articles, and also interpretive reviews of the literature. We also encourage short articles. The Review's policy is to have less than a three month turnaround time for reviewing articles for publication. We encourage all participants of the New York Economics Association Annual Conference to submit their papers to the Review.

NEW YORK STATE ECONOMICS ASSOCIATION SUBMISSION OF PAPERS FOR THE ONLINE PROCEEDINGS

Participants of the New York Economics Association annual conference may submit their paper to the Online Proceedings editor for publication. The Proceedings volume is edited by Richard Vogel at State University of New York at Farmingdale and will be published in the Spring of 2014. Papers must arrive at the office of the Proceedings editor by January 20, 2014. Papers should be submitted electronically to Richard.vogel@farmingdale.edu. The editor reserves the right to include only those articles in the Proceedings that reflect the standards of the New York State Economics Association. Papers are limited to ten pages, including tables, figures, and appendices. The paper must be submitted using Microsoft Word. Papers in any other format, including WordPerfect, will not be accepted. If you have to convert a file to word, check that quotation marks ("), apostrophes ('), and other symbols come out as intended after the conversion (including all mathematical equations). If they do not, change them manually before submitting the paper. Formatting Guidelines can be found at the NYSEA website (www.nysea@bizland.com). All papers must conform to the guidelines to be considered for publication.

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