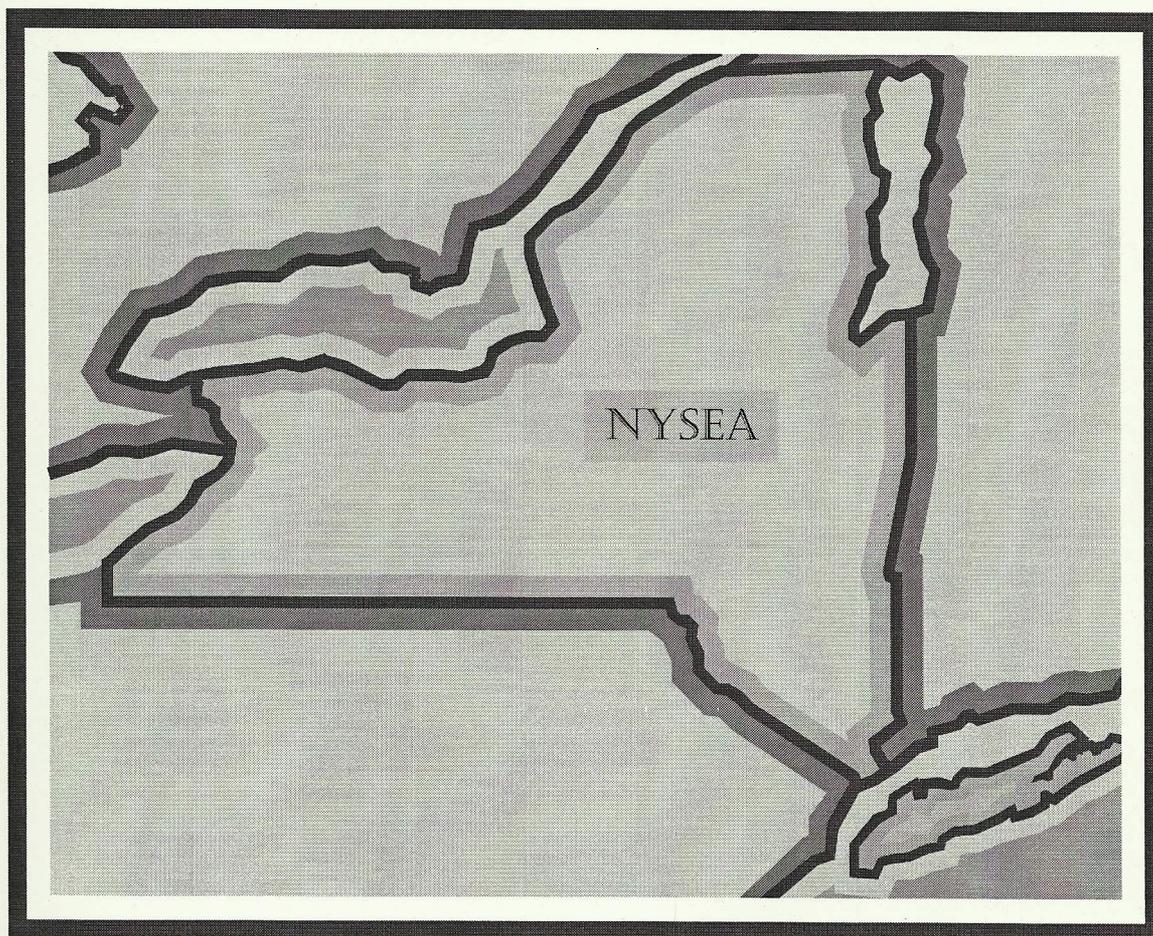


# NEW YORK ECONOMIC REVIEW

FALL 2010



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*VOLUME XLI*

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## EDITORIAL

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.

## MANUSCRIPT GUIDELINES

1. Please submit three copies of a manuscript.
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3. All charts and graphs *must* be reproduction quality (Microsoft Word or Excel).
4. Footnotes should appear at the end of the article under the heading of "Endnotes."
5. Citations in the text should include the author and year of publication, as found in the references, in brackets. For instance (Marshall, 1980).
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# The Slope of the U.S. Nominal Treasury Yield Curve Unemployment and Stability of Wage Determination: United States versus New York State

Jonathan Ohn<sup>\*</sup>, John Okpara<sup>\*\*</sup>, and Martina Vidovic<sup>\*\*\*</sup>

## ABSTRACT

We find the Phillips-type model performs well in explaining wage adjustment for US non-farm business, US manufacturing, and NY manufacturing sector, showing a typical adjustment to price inflation expectation and labor market tightness. While the basic wage model shows evidence of a structural shift for the post-1991 period, this is not evident in the adjusted models for both US non-farm business and NY manufacturing, implying that the observed structural shift for the post-1991 period is likely to be the result of model mis-, or under-specification. The effect of the fraction of unemployment due to permanent job loss on wage inflation appears to be manufacturing-specific, while a smaller adjustment to price inflation expectation appears to be state-specific. On the other hand, the significant effect of the percent of adults unemployed appears to be a national phenomenon.

## Introduction

Historically, both price and wage inflation followed a fairly predictable pattern over the business cycle, increasing during an economic expansion, peaking slightly after the beginning of a recession, and then continuing to decrease through the early stage (first or second year) of a recovery. However, during the 1990s recovery, the United States (US) exhibited unusually low and declining price and wage inflation despite strong growth and a decreasing unemployment rate. Several studies showed that the traditional Phillips curve model consistently overpredicted actual inflation (Duca, 1996; Low and Rich, 1997; Hyclak and Ohn, 2001). Duca (1996) found that overprediction by the Phillips curve was due to unusually high duration of unemployment, while Low and Rich (1997) linked it to unusually low wage growth. Hyclak and Ohn (2001) confirmed the findings by Duca and Low and Rich that the traditional Phillips curve model overpredicted the inflation rate in the 1990s and showed that the high duration of unemployment was due to an increase in the fraction of older permanent job losers.

While most of the studies on wage adjustment have examined national data, usually from the Current Population Survey, relatively little attention has been paid to regional or local labor markets in the US even though many labor markets are distinctly local in character. Topel (1994) and Karoly and

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Klerman (1994) examine changes in distribution of earnings at the regional and state levels. Borjas and Ramey (1995) examine the impact of trade sensitivity on changes in college earnings premium in a sample of metropolitan areas. Ohn and Kramer (2007) examined wage adjustment for the state of Pennsylvania using a type of wage Phillips model. In this paper, we perform a comparative analysis on the structure of wage adjustment in the US and New York (NY) State. Particularly, this study examines the relationship between wage inflation and the unemployment rate for US nonfarm business, NY manufacturing, and the US manufacturing sector for the period 1975-2006, and the stability of the Phillips model during the post 1991 recovery and the first half of 2000s. We investigate whether the observed low wage inflation can be explained by three characteristics of unemployment spells: the duration of unemployment, the fraction of adults who are unemployed and the fraction of unemployment due to permanent job loss. We find that the Phillips-type model performs well in explaining wage adjustment for the U.S. non-farm business, U.S. manufacturing, and NY manufacturing sector, showing a typical adjustment to price inflation expectation and labor market tightness. Inclusion of demographic variables of unemployment in the adjusted model alters the prediction of wage inflation by the basic Phillips model implying that the evidence of a structural shift for the post-1991 period is likely the result of model mis- or under-specification.

The remainder of the paper is organized as follows. Section II describes the empirical model and the data. Section III discusses: 1) the results of estimating three Phillips-type models; 2) the issue of model stability for those models; and 3) whether the difference between the US and NY State is industry-specific or state-specific. Section IV concludes.

## II. Empirical Model and Data

Following Alogoskoufis and Smith (1991) and Hyclak and Ohn (1997, 2001), we examine the quarterly wage adjustment process over the period 1975-2006 using the Phillips-type model:

$$\Delta w_t = \beta_0 + \beta_1 \Delta w_{t-1} + \beta_2 E(\text{inf}_t) + \beta_3 U_{t-1} + e_t$$

where  $\Delta w_t$  is quarter-to-quarter wage inflation,  $E(\text{inf}_t)$  is the expected price inflation, and  $U_{t-1}$  is the lagged unemployment rate. We capture the expected price inflation by the lagged actual price inflation,  $\Delta p_{t-1}$  and by the expected rate of consumer price inflation projected at the end of the preceding period,  $E(\text{inf}_t)$ . A number of wage studies based on Phillips-type model(s) include several lags of actual inflation rates to control for inflation expectation. While inclusion of a series of lags is designed to describe the continuous adjustment process toward an unbiased expected inflation (backward-looking), the expected inflation used in this paper is computed based on the forecasted one-year GDP price index (forward-looking). The computed expected inflation is measured at the end (beginning) of the previous (current) quarter for the next one-year period and is supposed to already reflect any influencing factors such as previous inflation expectation, a series of past actual inflations, and other influential factors. In order to allow for the assumption that the aggregate unemployment rate may not fully reflect the recent labor market change as suggested by Duca (1996) and Hyclak and

Ohn (2001), in the adjusted model, we include three demographic factors of unemployment: the duration of unemployment (*DUR*), the percent of unemployed adult population ages 25 and older (*R25*), and the fraction of unemployed due to permanent job loss, (*RJL*). The adjusted model is given by

$$\Delta W_t = \beta_0 + \beta_1 \Delta w_{t-1} + \beta_2 E(\text{inf}_t) + \beta_3 U_{t-1} + \beta_4 DUR_{t-1} + \beta_5 R25_{t-1} + \beta_6 RJL_{t-1} + e_t$$

Following Valetta (1997, 1998) and Dijk and Folmer (1999), we hypothesize that longer duration of unemployment will put downward pressure on the reservation wage a worker is willing to accept. While skill-biased technological change and corporate downsizing may not have a serious impact on younger workers, they are likely to have a more significant impact on adult (older) workers. We expect to find that the higher the percentage of unemployed adults, the lower will be the reservation wage. Similarly, since permanent job losers, on average, experience longer unemployment spells compared to those who are unemployed for other reasons, we anticipate that the higher the fraction of permanent job-losers, the lower will be the reservation wage. Thus, we expect a significant negative relationship between wage inflation and the duration of unemployment, the percentage of unemployed adults and the percentage of permanent job losers.

The wage data and the unemployment rate for the US and NY state are from the Bureau of Labor Statistics (BLS) website. The wage data are the total hourly wages and salaries for national non-farm business, national manufacturing, and the NY state manufacturing-sector. The three demographic unemployment variables are the average number of weeks unemployed, the percentage of unemployed adults who are 25 years and older, and the percentage unemployed due to permanent job loss. The demographic variables are from the Current Population Survey, while the expected rate of price inflation is from the Survey of Professional Forecasters conducted and reported by the Federal Reserve Bank of Philadelphia. The expected rate of price inflation is computed based on the forecasted one-year GDP price index at the end (beginning) of previous (current) period and the computed expected inflation is for the next one-year period including current period (quarter).

### III. Estimation Results

#### Regression Results of Three Phillips-Type Wage Models

The upper panel of Table 1 shows the results for three different versions of the Phillips-type wage model. Models 1 and 2 show the results of the basic model. In Model 1 we capture the price inflation expectation by lagged actual price inflation, and in Model 2 by expected price inflation. Model 3 adds the three demographic labor market variables.

All three models show that the adjustment to price inflation expectation is a major factor in wage inflation. In all three models, the coefficient of the price inflation expectation is positive and statistically significant for both the US nonfarm business and NY manufacturing. However, the expected price inflation based on the Survey of Professional Forecasters (Models 2 and 3) seems to be a better measure of the price inflation expectation than the lagged actual price inflation (Model 1). When we

**Table 1. Test Results on the Wage Phillips Curve Model for the US Nonfarm Business and NY Manufacturing Sector, 1975-2006.****Regression Results**

Variable	US			NY		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	4.720** (1.058)	5.212** (1.079)	19.193** (3.481)	-0.344 (0.326)	-0.015 (0.292)	2.504* (1.803)
$\Delta W_{t-1}$		0.101 (0.088)	0.055 (0.091)		0.064 (0.091)	0.045 (0.091)
$E(inf)^a$	0.407** (0.062)	1.051** (0.161)	0.643** (0.188)	0.060** (0.018)	0.225** (0.042)	0.156* (0.067)
$U_{t-1}$	-0.160 (0.164)	-0.744** (0.192)	-0.556* (0.248)	0.155** (0.049)	-0.007 (0.050)	-0.077 (0.065)
$DUR_{t-1}$			0.022 (0.115)			-0.028 (0.037)
$R25_{t-1}$			-0.201** (0.064)			-0.018 (0.029)
$RJL_{t-1}$			-0.021 (0.048)			-0.023* (0.011)
$Adj-R^2$	0.232	0.389	0.502	0.168	0.334	0.382
$DW$	1.607	2.005	2.006	1.534	1.946	2.008

**Results of the Chow Test on the Model Stability for the Post-1991 Period**

Variable	US			NY		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
F-statistic	9.817** [0.000]	1.925+ [0.089]	1.582 [0.146]	6.324** [0.000]	2.176+ [0.076]	1.329 [0.244]

<sup>a</sup>  $E(inf)$  is the inflation expectation of general price level.  $E(inf) = P_{t-1}$  = lagged actual price inflation (BLS) in Model 1, and  $E(inf) = E(P_t)$  = expected price inflation from the Survey of Professional Forecasters at the Federal Reserve Bank of Philadelphia.

Standard errors of the coefficients in (parentheses). p-values are in [parentheses].

\*\* significant at the 1% level, \* significant at the 5% level, and + significant at the 10% level.

replace the lagged price inflation with the expected price inflation (Model 1 versus Model 2), the coefficient increases from 0.407 to 1.051 for the US, and from 0.060 to 0.225 for the NY State. At the same time the adjusted  $R^2$  increases from 0.335 to 0.436 for the US model and from 0.209 to 0.381 for the NY model. Interestingly, the magnitude of wage adjustment to price inflation expectation is much smaller for the NY manufacturing wage.

The coefficient on expected price inflation variable is larger in magnitude for the US non-farm business than for the NY manufacturing sector (1.051 versus 0.225 in Model 2, and 0.643 versus 0.156 in Model 3). The persistence of wage inflation as measured by the lagged dependent variable (Models 2 and 3) does not have a statistically significant impact on the wage adjustment process. We tested the sensitivity of our results by including lags of expected inflation. However, once we include the longer lags, the coefficients on both current and lagged expected inflation become statistically insignificant.

The coefficient on the lagged unemployment rate in Model 1 is negative, albeit statistically insignificant for the US non-farm business and positive and statistically significant for the NY manufacturing sector. This indicates that the labor market forces do not have an effect on the US non-farm business, and contrary to our expectation, have a positive effect on the NY manufacturing wage. However, once we replace the lagged price inflation by the expected price inflation (Model 1 versus Model 2), the coefficient on the unemployment rate for the US non-farm sector becomes statistically significant and is much larger in magnitude (-0.160 in Model 1 versus -0.744 on Model 2) indicating a typical strong negative effect of the labor market force. This is consistent with the findings by Duca (1996) and Hyclak and Ohn (2001). On the other hand, for the NY manufacturing sector, the coefficient on the unemployment rate switches from positive and statistically significant in Model 1 to negative and not statistically significant in Model 2 indicating that labor market forces have no effect on wage adjustment. When we include three demographic unemployment variables in Model 3, we find that the coefficients on unemployment rate and the percent of unemployed adults who are 25 and older are statistically significant and negatively affect the national wage. The coefficient on the aggregate unemployment rate is smaller in magnitude in Model 3 than in Model 2. It seems that the higher fraction of unemployed adults captures a part of the effect of labor market force which is not represented by the aggregate unemployment rate. For the NY manufacturing wage, only the percent of unemployment due to permanent job loss shows a statistically significant and negative effect on wage adjustment.

Our results indicate that while both the national non-farm business and NY manufacturing wage show a significant adjustment to expected price inflation, the national wage adjustment to long-run labor market force can be explained by the aggregate unemployment rate and the percent of adult unemployment, while the NY manufacturing wage adjustment is driven by the fraction of

unemployment due to permanent job loss. Although the effect of expected price inflation is statistically significant for NY manufacturing, it is quite lower in magnitude compared to the national model.

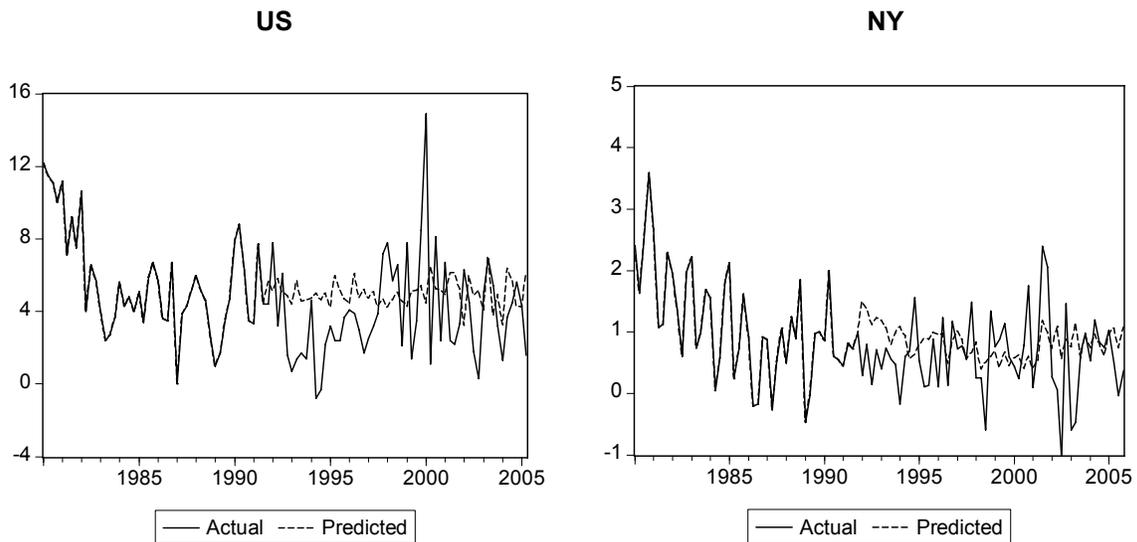
**Model Stability**

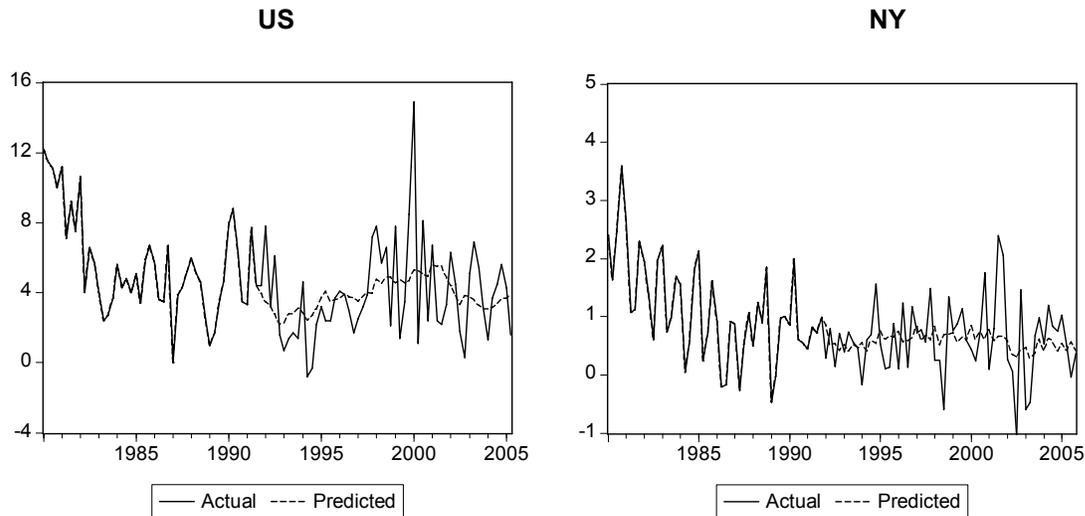
The lower panel of Table 1 shows the result of the Chow test for the model stability over the post-1991 period. The basic model (Model 1) shows significant evidence of a structural shift for the post-1991 period for both the US and NY. When we replace the lagged actual price inflation with the expected price inflation (Model 2), the evidence of a structural shift for the post-1991 period becomes much smaller (the F statistic is significant at the 10 percent for both US and NY State). On the other hand, once we include the three demographic unemployment variables (Model 3), the evidence of a structural change disappears in both the US and NY State. This suggests that the previous finding of over-prediction or a structural shift by the wage Phillips-type model in the 1990s' is a result of model mis-specification or under-specification rather than a result of an actual structural shift.

Figure 1 compares the actual and forecasted wage inflation for the post-1991 period. The graphs in Panel A show the actual and forecasted wage inflation for the US non-farm business and NY manufacturing based on Model 1. In the case of both the US and NY, the model consistently overpredicts wage inflation for the post-1991 period but only slightly for the mid-2000s. However, the graphs in Panel B, which compare actual and forecasted wage inflation based on Model 3, do not show any significant over-prediction pattern for the US and NY. The regression and forecast results confirm our finding that the observed structural shift for the 1990s is a result of model mis- or under-specification and not a result of an actual shift.

**Figure 1. Actual vs. Forecasted Wage Inflation based on Models 1 and 3: US Non-farm Business vs. NY Manufacturing Sector**

**A. Actual vs. Forecasted Wage Inflation Based on Model 1, 1992-2006.**



**B. Actual vs. Forecasted Wage Inflation Based on Model 3, 1992-2006****Difference between the US and NY Results – Industry-specific or State-specific?**

The above results raise an interesting question: Are the differences between the national and the NY results sector-specific or state-specific? To answer the question, we examine the wage adjustment process for the US manufacturing sector over the same period. The results are shown in Table 2. The basic model (Model 1) shows a significant adjustment to lagged price inflation but not to employment. The coefficient on the lagged unemployment rate is only marginally significant and has a positive sign. The adjusted models (Models 2 and 3) show a typical positive and significant adjustment to expected price inflation, a negative and significant adjustment to unemployment rate, and a significant positive adjustment to wage inflation persistence. This is different from the results for the US non-farm business and NY manufacturing sector. Recall that the coefficient on the lagged wage inflation variable was not significant for the US non-farm business and NY manufacturing sector (Table 1, Model 2). In Model 3, the significant effect of the unemployment rate found in Model 2 is captured by the fraction of adult population that is unemployed (found in the US non-farm business model) and by the percent of unemployed due to permanent job loss (found in the NY manufacturing sector). The magnitude of the adjustment to expected inflation (0.426) is in between the values for US non-farm business (0.643) and NY manufacturing (0.156).

These findings suggest that for the manufacturing sector, the wage adjustment to unemployment is partially due to permanent job loss at both the NY state and national level. On the other hand, the wage adjustment to unemployment due to a larger fraction of adult unemployment appears to be nation-specific.

**Table 2. Test Results on the Wage Phillips Curve Model for the US Manufacturing Sector, 1975-2006**

**Regression Results**

Variable	Model 1	Model 2	Model 3
Constant	0.087 (0.921)	1.984* (0.811)	13.903** (4.496)
$\Delta W_{t-1}$		0.395** (0.081)	0.219* (0.090)
$E(inf)^a$	0.397** (0.056)	0.764** (0.146)	0.426* (0.204)
$U_{t-1}$	0.363+ (0.244)	-0.354* (0.149)	-0.018 (0.203)
$DUR_t$			-0.059 (0.092)
$R25_{t-1}$			-0.176* (0.068)
$RJL_{t-1}$			-0.045+ (0.025)
$Adj-R^2$	0.344	0.546	0.638
$DW$	1.496	2.019	1.913

**Results of the Chow Test on the Model Stability for the Post-1991 Period**

F-statistic	5.104** [0.000]	2.379* [0.042]	2.182+ [0.071]
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<sup>a</sup>  $E(inf)$  is the inflation expectation of consumer price.  $E(inf) = P_{t-1}$  = lagged actual price inflation in Model 1, and  $E(inf) = E(P_t)$  = expected price inflation from Survey of Professional Forecasters at the Federal Reserve Bank of Philadelphia.

Standard errors of the coefficients in (parentheses). p-values are in [parentheses].

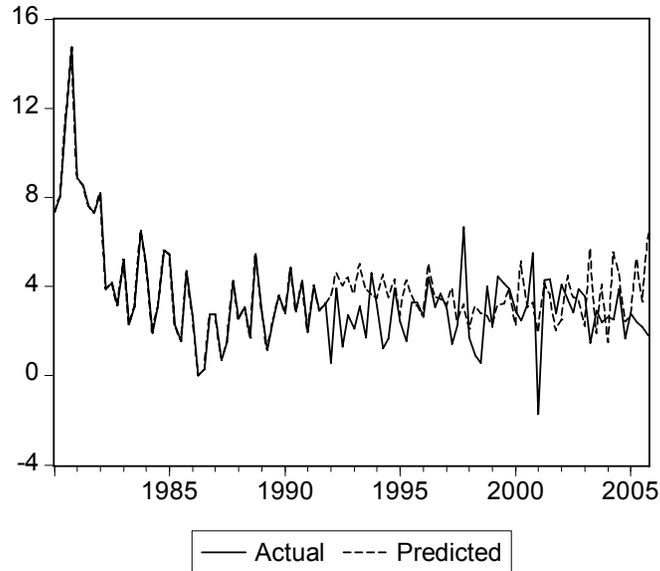
\*\* significant at the 1%, \* significant at the 5%, + significant at the 10%.

The test for model stability indicates that the evidence of a structural shift for the post-1991 period based on the basic wage model (Model 1) for the US manufacturing sector does not disappear in two adjusted models (Models 2 and 3). Even though the magnitude of the test statistic decreases in the two adjusted models, it is still statistically significant at the 5 percent level in Model 2 and at the 10 percent level in Model 3.

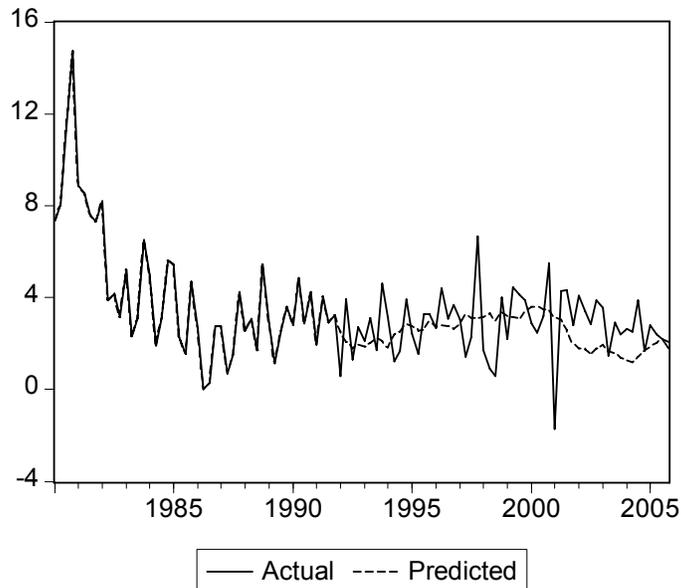
Figure 2 compares the actual and the forecasted values of wage inflation for the US manufacturing sector. The basic model (Model 1) generally overpredicts the wage inflation during the

**Figure 2. Actual vs. Forecasted Wage Inflation Based on Models 1 and Model 3: US Manufacturing Sector**

**A. Actual vs. Forecasted Wage Inflation Based on Model 1, 1992-2006**



**B. Actual vs. Forecasted Wage Inflation Based on Model 3, 1992-2005**



early- to mid-1990s and the mid-2000s, while the adjusted model (Model 3) shows a slight under-prediction for the mid-2000s, which resulted in the marginally significant Chow test statistics for Model 3.

#### IV. Conclusion

Recently, researchers have questioned the stability of the Phillips model in predicting inflation. The post 1991 recovery period resulted in low rates of price and wage inflation despite strong growth and a declining unemployment rate. In this paper, we examined wage adjustment to price inflation expectation and labor market forces as represented by the unemployment rate and three demographic factors of unemployment for the US non-farm business, NY manufacturing, and the US manufacturing sector. Our results suggest that Phillips-type models do a good job in explaining wage adjustment for both the US non-farm sector and the US and NY manufacturing sectors.

We find that the rise in fraction of the adult population which is unemployed and the rise in the fraction of unemployment due to permanent job loss can explain the behavior of wage inflation during the post 1991 better than the unemployment rate alone. The previously observed structural shift for the post-1991 period seems to be a result of model mis- or under-specification for the US non-farm business and the NY manufacturing but not for the US manufacturing sector. These results suggest that any analysis of US economy during the post 1990 recession must consider structural changes in unemployment.

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# Forecasting the New York State Economy with “Terraced” VARs and Coincident Indices

Eric Doviak\* and Sean MacDonald\*\*

## ABSTRACT

This paper introduces “Terraced” Vector Autoregressive (VAR) models, an innovative twist on traditional VAR modeling, which allows the econometrician to simultaneously forecast both exogenous and endogenous variables and the confidence intervals around those forecasts.

In an application of our Terraced VAR framework, we have estimated coincident indices of economic activity for the United States, New York State and the six largest metropolitan areas of New York State and incorporated them into Terraced VARs, which forecast the unemployment rate, total non-farm employment, real wages and average hours worked in manufacturing in those regions.

## I. Introduction

Forecasting regional economic variables poses a difficult task because the data series often exhibit negative first-order serial correlation (i.e. the series looks “jagged” or “saw-toothed”). Perhaps more importantly, the frequent fluctuations in the series make it difficult to discern whether a one-month increase in the unemployment rate or a one-month decrease in non-farm employment represent a deterioration of local economic conditions or simply represent the natural fluctuations of the series. Figures 1 and 2, which plot Rochester’s unemployment rate and non-farm employment level, illustrate the point.

To overcome this difficulty, we used Kalman’s (1960) filtering algorithm to estimate a coincident index of labor market activity from the unemployment rate, non-farm employment, average hours worked in manufacturing and real wages. Such an index of Rochester’s economy is shown in Figure 3.

Because the index does not exhibit negative first-order serial correlation, it follows a simple autoregressive process, which is relatively easy to forecast. And because the coincident index was estimated from the economic variables of interest to us, it is highly correlated with those variables and allows us to forecast them with more accuracy than we could achieve if we had not incorporated the coincident index into our forecasting models.

On a monthly basis, we use our forecasting model to produce reports on the state of New York’s labor market for the New York State Banking Department, which sponsored our research. Readers of

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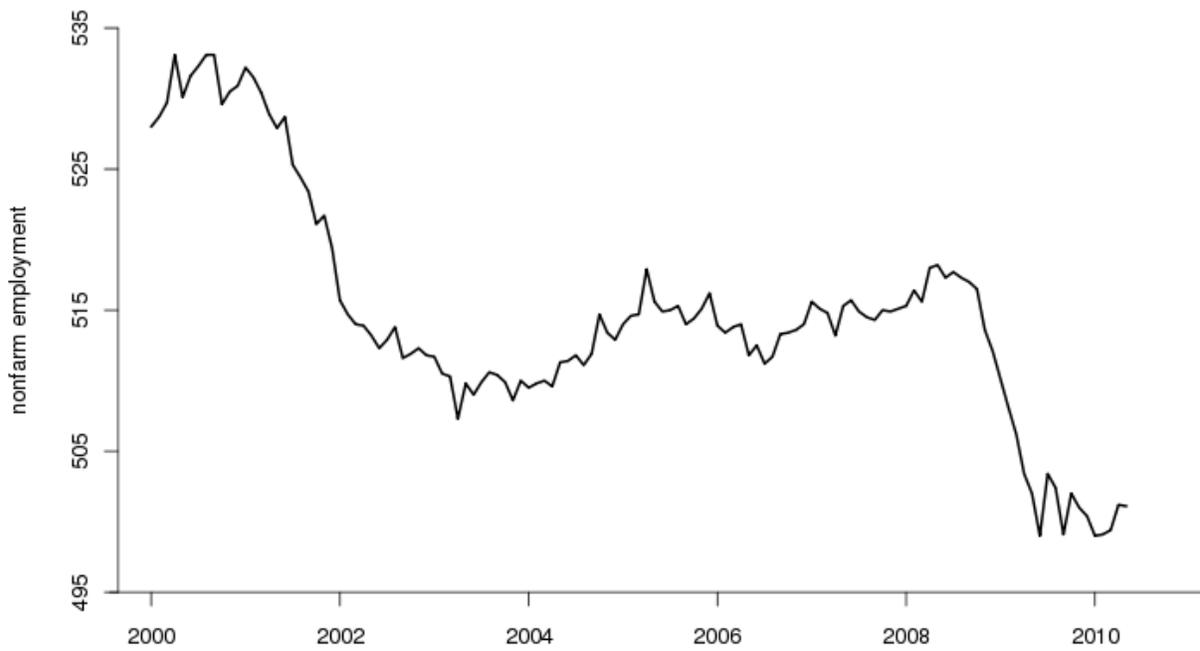
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**Figure 1: Rochester Unemployment Rate (seasonally adjusted)**



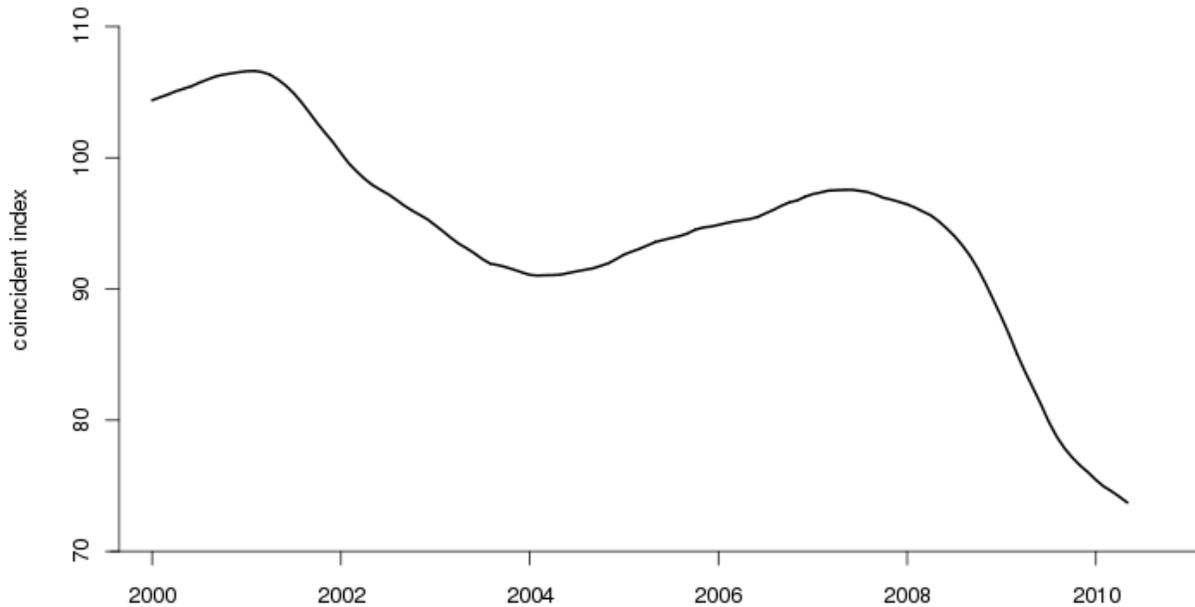
Note: The series depicted above ends in May 2010.

**Figure 2: Rochester Nonfarm Employment (seasonally adjusted)**



Note: The series depicted above ends in May 2010.

Figure 3: Coincident Index of the Rochester Economy



Note: The data used to generate the coincident index depicted above ends in May 2010.

the reports appreciate the visual smoothness of the coincident index because it allows them to quickly discern the trend in regional labor market activity.

Section II of this paper introduces and defines a methodology for constructing a coincident index of labor market indicators for the United States, New York State and the six largest metropolitan statistical areas (MSAs) of New York State<sup>1</sup>. In explaining what a coincident index is, the paper also describes the coincident indices of national, state and regional economic activity that other economists have developed.

We did not develop coincident indices for their own sake. We developed them for the purpose of forecasting variables that depend on the state of the labor market, such as banks' non-current loans (a topic of particular interest to the Banking Department). To that end, we incorporated the coincident indices into "terraced" vector autoregressive (VAR) models, which can be used to forecast variables of interest, such as the unemployment rate and rates of foreclosure on residential mortgages.

In other words, we hypothesized that homeowners' difficulties in the labor market have been a major contributor to the recent increase in mortgage delinquency. We did find a strong correlation between our coincident indices and non-current loans, but we are reluctant to publish those findings because the FDIC's Statistics on Depository Institutions (our source of bank financial data) is only available on a quarterly basis since 2003 and on an annual basis since 1992.

The "terraced" VAR methodology, which we describe in section III, is our primary contribution to the economic literature. Unlike traditional VAR forecasting, "terraced" VARs do not require exogenous and endogenous variables to be forecast in two separate steps. Instead, the exogenous and

endogenous variables are forecast simultaneously, which allows the econometrician to obtain confidence intervals that depend only on the respective “predictor” variables.

For example, suppose that the New York City coincident index depends on past values of the national coincident index, but the reverse is not true. In such a simple, two-variable “terraced” VAR, the confidence interval around the forecast of the New York City index would depend on the residual variance of its regression equation, the residual variance of the national index’s regression equation and the covariance between them. By contrast, the confidence interval around the forecast of the national index would only depend on the residual variance of its own regression equation. Consequently, the “terraced” VAR methodology allows us to simultaneously compute the appropriate confidence intervals around both the New York City and national coincident indices.

Thus, the paper seeks to extend and build upon the existing literature on state-level coincident indices, while introducing new applications, such as incorporating the coincident indices into “terraced” VARs to forecast “key economic variables.” The indices can therefore help policymakers anticipate the future course of key economic trends. For example, the coincident indices can be used to forecast unemployment rates, total employment as well as indicators of banks’ financial health (e.g. rates of foreclosure filings and non-current loans). By including the forecast confidence intervals, we also provide policymakers with an indication of how accurate they can expect our forecasts to be. These uses of our methodology are briefly discussed in the conclusion of our paper, section IV.

## **II. Coincident Indices**

### **1. Survey of Literature**

In common speech, people often refer to the “state of the economy” with statements such as: “The economy is strong,” or “The economy is in bad shape right now.” As a question of measurement however, one must wonder what they are referring to. Are they referring to growth of real Gross Domestic Product (GDP)? Are they referring to growth of real household income? Are they referring to job growth? Are they referring to the unemployment rate?

Assuming that they are referring to some combination of those measures, how then do we evaluate a period in which real GDP grows, but the unemployment rate rises? Is the state of the economy “strong” or “weak?”

Obviously, one can easily define a weighted average of such measures, but what are the appropriate weights to apply to each measure? Should those weights be constant over time? Kacapyr’s (2010) Tompkins County index, for example, weights each element in inverse proportion to its volatility and adjusts the weights periodically. One can also imagine other reasons why the weights should not be constant over time. For example, if the economy is experiencing a structural shift, in which the manufacturing sector shrinks as the service sector grows, then it hardly makes sense to apply the same weight to manufacturing sector employment over time.

In addressing such questions, Stock and Watson (1989) made an original and valuable contribution to the econometric literature by observing that each of the measures described above depends on the underlying “state of the economy” and the particular characteristics that define each measure. They then used Kalman’s (1960) filtering algorithm to identify the unobservable “state of the economy” in a single index, called the “coincident index.”

Visually significant decreases in Stock and Watson’s original coincident index matched the beginnings and endings of recessions, as defined by the National Bureau of Economic Research (NBER). Visually significant increases, of course, corresponded to economic expansions. Stock and Watson also used a Vector Auto-Regression (VAR) model to forecast changes in the coincident index. The forecast of the coincident index is called the “leading index.”

More recently, two economists at the New York State Division of the Budget, Megna and Xu (2003), used Stock and Watson’s methodology to develop coincident and leading indices for the New York State economy, which they then used to forecast changes in state tax revenue.

There is major difference between Stock and Watson’s index and Megna and Xu’s index however. Specifically, Stock and Watson were interested in developing an index based on co-movements in several macroeconomic time series, whereas Megna and Xu were interested in forecasting state tax revenue. Consequently, they used different data series to develop their indices.<sup>2</sup>

Economists at the Federal Reserve Bank of New York have also developed a coincident index of the New York State economy. Orr et al. (1999) developed such an index to predict changes in the regional economy that do not necessarily coincide with national trends.<sup>3</sup>

A recent update of their index conducted by Bram et al. (2009) suggests that the New York regional economy remained far more resilient than the national economy (in the sense that the New York region entered the current recession several months later than the nation as a whole). They also found that New York State’s economic activity peaked in February 2008, while New York City’s continued to expand through June 2008. They also note that New York City’s economy has already experienced a “steeper downturn than a number of metropolitan areas in upstate New York.”

Such trends also appear in our own indices. Our indices suggest that the United States entered the current economic recession almost one year before the economies of New York State and New York City. Specifically, our indices date the national recession as beginning in March 2007, while New York State and New York City entered recession in May 2008 and March 2008 respectively.

More broadly, Crone and Clayton-Matthews (2005) applied Stock and Watson’s methodology to estimate a consistent set of coincident indicators for all 50 states. They developed their indices because the considerable lag with which the Bureau of Economic Analysis releases Gross State Product (GSP) series inhibits timely monitoring of state economic trends. In developing their index, they also found that the indices are a useful for comparing “the length, depth, and timing of recessions at the state level.”

The Federal Reserve Bank of Philadelphia (2009) argues that Crone and Clayton-Matthews' state coincident indices are comparable across states because they are generated from a consistent set of models and variables, but we remain skeptical. Specifically, we suspect that some of the indices may appear more volatile than others because the parameter values in their filters differ across states.

Even if they are correct however, the fact that there is less data available to us at the sub-state level than at the national and state level would prevent us from constructing an index of regional economic activity that is comparable to a state or national index unless we were willing to discard valuable data.

Consequently, the index that we develop for one region is not directly comparable to another's because the coincident indices do not have a common unit of measurement. New York City's index is measured in "New York City coincident units," while Rochester's index is measured in "Rochester coincident units."

## 2. Data Used to Estimate the Coincident Index

With two exceptions, the data that we used to estimate the coincident index were the same four data series that Crone and Clayton-Matthews (2005) used to develop coincident indices for all 50 states. Three of the four series that Crone and Clayton-Matthews used – nonagricultural payroll employment, the unemployment rate and average hours worked in manufacturing – are monthly data series from the US Bureau of Labor Statistics.

Although the unemployment rate is generally identified as a lagging indicator of economic activity, it is an appropriate variable to use when estimating the *current* state of the labor market. Moreover, its use as a coincident indicator of economic activity is consistent with the models established in the earlier works of Stock and Watson (1989), Orr et al. (1999), Megna and Xu (2003), and Crone and Clayton-Matthews (2005).

Because the fourth series that Crone and Clayton-Matthews used, the U.S. Bureau of Economic Analysis' quarterly real wages and salary disbursements series, is not available at the sub-state level, we calculated real wages by adjusting the U.S. Bureau of Labor Statistics' total wage series for inflation with the U.S. consumer price index. For consistency, we also used the total wage series in our estimates of the U.S. and New York State coincident indices.

The fact that the total wage series is quarterly, while the other series are monthly, does not pose a problem. In their paper, Crone and Clayton-Matthews show that interpolation is not necessary to handle mixed monthly and quarterly series. Instead, they show that the Kalman Filter can be adapted to handle any missing data simply by altering the dimensions of the relevant matrices. In fact, Petris' (2009) "dlm" package for R (R Development Core Team, 2008), which we used to implement the Kalman Filter, is designed to handle missing data.

In a second departure from Crone and Clayton-Matthews' framework, we did not use average hours worked in manufacturing in our sub-state coincident indices because the series is not available

at the sub-state level. We also did not use the real wage series in our estimates of the Rochester and Buffalo-Niagara Falls coincident indices because the extreme volatility of those series inhibited our ability to estimate the parameters of the Kalman Filter when we tried to include them.

Additionally, we used the US Census Bureau's X-12-ARIMA seasonal adjustment software (2007) to seasonally adjust the New York State "average hours" series, all of the quarterly wage series and the sub-state unemployment rates.

Finally, to account for serial correlation in the data series, we took differences of the unemployment rate series and log differences of the other series. Differencing also enabled us to overcome the problems associated with the change in industrial classification from SIC to NAICS, which was implemented by the U.S. Bureau of Labor Statistics in 1990. Since both classifications attempted to measure the same economic variable, we assumed that the log-differences of the two classifications are highly correlated with each other and switched from SIC to NAICS at the earliest possible point (i.e. from 1990 onward).

### 3. Estimation of the Coincident Index

To implement the Kalman Filter, we used a structure based loosely on the one used by Megna and Xu (2003)<sup>4</sup>. Specifically, we used the following structure for the measurement equation:

$$\begin{bmatrix} \Delta unemp_t \\ \Delta \ln(emp)_t \\ \Delta \ln(wages)_t \\ \Delta \ln(hours)_t \end{bmatrix} = \begin{bmatrix} \alpha_0 & \alpha_1 & \alpha_2 & \alpha_3 \\ \beta_0 & \beta_1 & 0 & 0 \\ \gamma_0 & \gamma_1 & \gamma_2 & 0 \\ \delta_0 & \delta_1 & 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta c_t \\ \Delta c_{t-1} \\ \Delta c_{t-2} \\ \Delta c_{t-3} \end{bmatrix} + \begin{bmatrix} u_{unemp,t} \\ u_{emp,t} \\ u_{wages,t} \\ u_{hours,t} \end{bmatrix} \quad (1)$$

and the following structure for the transition equation:

$$\begin{bmatrix} \Delta c_t \\ \Delta c_{t-1} \\ \Delta c_{t-2} \\ \Delta c_{t-3} \end{bmatrix} = \begin{bmatrix} \phi_0 & \phi_1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta c_{t-1} \\ \Delta c_{t-2} \\ \Delta c_{t-3} \\ \Delta c_{t-4} \end{bmatrix} + \begin{bmatrix} v_t \\ 0 \\ 0 \\ 0 \end{bmatrix}, \quad (2)$$

where  $\Delta c_t$  is the change in the coincident index at time  $t$  and the residuals  $u_{i,t}$  and  $v_t$  are assumed to have zero mean and constant variance.

As mentioned in section II.2, average hours worked in manufacturing is not available at the sub-state level, so the last row of equation 1 does not appear in the local economies' measurement equations.

We also used a slightly different structure for the measurement and transition equations of the Rochester and Buffalo-Niagara Falls Metropolitan Statistical Areas (MSAs). As mentioned in section II.2, we did not use the real wage series in our estimates of their coincident indices. We also found that a different structure worked better for their economies. Specifically, with the data for the Rochester

and Buffalo-Niagara Falls MSAs we used the following structure for the measurement equation:

$$\begin{bmatrix} \Delta unemp_t \\ \Delta \ln(emp)_t \end{bmatrix} = \begin{bmatrix} \alpha_0 & \alpha_1 & \alpha_2 & \alpha_3 \\ \beta_0 & \beta_1 & \beta_2 & 0 \end{bmatrix} \begin{bmatrix} \Delta C_t \\ \Delta C_{t-1} \\ \Delta C_{t-2} \\ \Delta C_{t-3} \end{bmatrix} + \begin{bmatrix} u_{unemp,t} \\ u_{emp,t} \end{bmatrix} \quad (3)$$

and the following structure for the transition equation:

$$\begin{bmatrix} \Delta C_t \\ \Delta C_{t-1} \\ \Delta C_{t-2} \\ \Delta C_{t-3} \end{bmatrix} = \begin{bmatrix} \phi_0 & \phi_1 & \phi_2 & \phi_3 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta C_{t-1} \\ \Delta C_{t-2} \\ \Delta C_{t-3} \\ \Delta C_{t-4} \end{bmatrix} + \begin{bmatrix} v_t \\ 0 \\ 0 \\ 0 \end{bmatrix}. \quad (4)$$

Although the transition equations are designed to yield a single index, Petris’ (2009) “dlm” package, which we used to implement the Kalman Filter, does not output a single index. Instead, it outputs four (one for each row of the transition equation). In practice however, each successive index contains the lagged values of the previous one and (after accounting for the lags) the differences between the four indices can safely be ignored.

#### 4. What the Coincident Index Tells Us

To evaluate the quality of our coincident indices, it is helpful to compare our national and New York State index with the national and New York State indices published by the Federal Reserve Bank of Philadelphia and with Megna and Xu’s (2003) New York State index. Figures 4 and 5 provide a visual comparison of our indices with those published by the Philadelphia Fed and the text of this section provides a qualitative comparison.<sup>5</sup>

As mentioned in Section II.1, visually significant decreases in the coincident index indicate that the economy is in recession. Consequently, the peaks and troughs in the index can be used to mark the beginnings and endings of economic recessions. Therefore, the periods during which our coincident index indicates that the economy was in recession should roughly correspond to the recessionary periods in their indices.

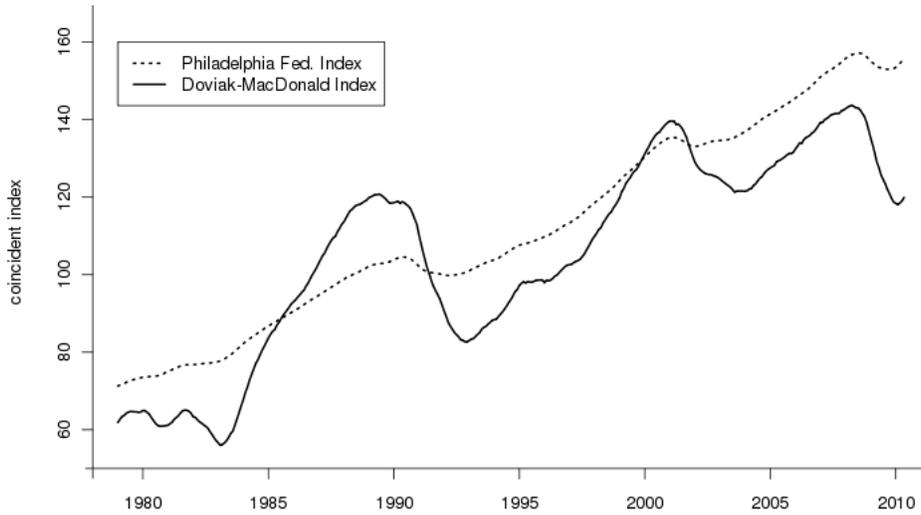
As Figures 4 and 5 show, our indices exhibit much more dramatic swings in labor market activity than the Philadelphia Fed’s indices do. This difference does not bother us. On the contrary, we feel that the dramatic swings in our indices more accurately reflect the state of the labor market.

For example, the value of the Philadelphia Fed’s index for the US economy was 158.55 in May 2010, which was roughly the same as the 158.66 reading in February 2006. The state of the labor market was very different at those two points in time however. After all, the unemployment rate was 4.9 percentage points higher and non-farm employment was 3.5 percent lower in May 2010 than it

was in February 2006. By contrast, our United States index value was 107.0 in February 2006 and 52.5 in May 2010.

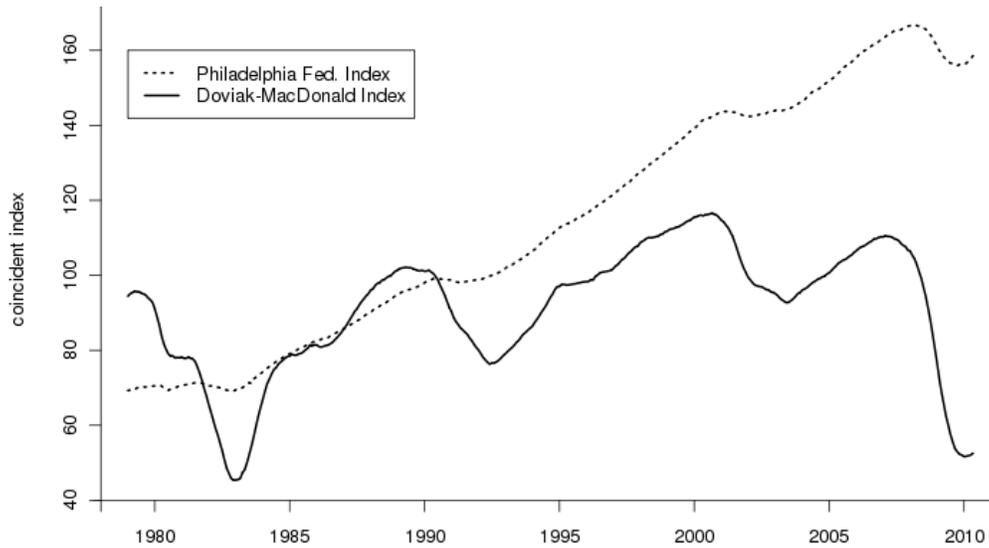
Similarly, the value of the Philadelphia Fed's index for the New York State economy was 155.32 in May 2010, which was roughly the same as the 155.32 reading in December 2007. Once again, the state of the labor market was very different in those two periods. New York's unemployment rate was 3.6 percentage points higher and its non-farm employment was 2.5 percent lower in May 2010 than it was in December 2007. Once again, our New York index more accurately reflects the change in the state of the labor market, as its index values were 142.5 in December 2007 and 119.9 in May 2010.

**Figure 4: Coincident Indices of the New York State Economy**



Note: The series depicted above ends in May 2010.

**Figure 5: Coincident Indices of the United States Economy**



Note: The series depicted above ends in May 2010.

More broadly, the Philadelphia Fed's indices do not account for the “jobless” recoveries that characterized the previous two recessions. By contrast, our indices exhibited longer periods of recession than the Philadelphia Fed's indices did, which suggests that our indices account for the structural changes that occurred in the US and New York State labor markets. The Philadelphia Fed's indices do not. In particular, our indices capture the effect that the manufacturing sector's decline has had on upstate labor markets since it began shrinking in 1990.

This effect of the manufacturing sector's decline is strikingly evident in our Rochester index which peaked in 2001 and never recovered from the subsequent recession (as can be seen in Figure 3).

Figure 4 provides a graphical comparison of our New York State index to the one developed by the Philadelphia Fed and illustrates the tendency of our index to show longer periods of recession. For example, our index indicates that the New York State economy entered a recession in October 1979 and did not recover until November 1980. By contrast, the Philadelphia Fed index indicates that that recession began in March 1980 and ended in July 1980, a mere four months in comparison with our 13 months. We were unable to obtain the data necessary to plot Megna and Xu's New York State index, but their paper states that the recession ran from March 1980 to September 1980.

All three New York State indices indicate that the next New York State recession began in September 1981, but our index and Megna and Xu's index indicate that it ended in February 1983, while the Philadelphia Fed index indicates that it ended three months earlier, in November 1982.

At the end of the 1980s, both our index and the Philadelphia Fed index suggest that New York State's economy plateaued for over a year before entering recession in the second quarter of 1990, but our index indicates that the recession lasted longer than the Philadelphia Fed index does. Specifically, our index indicates that it ended in September 1992, whereas the Philadelphia Fed index indicates that it ended in June 1992. By contrast, Megna and Xu's index shows a peak in June 1989 and a long recession that didn't end until November 1992.

Our index and the Philadelphia Fed index also show a common beginning to the New York State recession that began in February 2001, but once again our index indicates that it lasted longer than the Philadelphia Fed index does. Specifically, their index indicates that it ended in March 2003, while our index indicates that it ended in August 2003.

Figure 5 shows sharp differences between our index and the Philadelphia Fed's regarding when the U.S. economy enters recession and how long it lasts. Generally speaking, our index suggests earlier beginnings and longer durations of economic recessions than theirs. For example, our index indicates that the United States entered the current economic recession in March 2007, whereas the Philadelphia Fed index indicates that the national economic recession began in April 2008.

Similar discrepancies are also seen in the dating of other recessions as well. At the extreme, our index indicates that the previous national recession began in October 2000 and lasted 33 months, while the Philadelphia Fed index places its beginning at June 2001 and indicates that it lasted only eight months.

A similarly large difference exists in the dating of the national recession of the early 1990s. Our index indicates that it lasted from April 1990 to June 1992, whereas the Philadelphia Fed indicates that it lasted from October 1990 to May 1991.

The differences in the dating are smaller however when we compare the dating of the two recessions in the early 1980s. Our index indicates that the first one began in July 1979 and lasted 14 months, while the Philadelphia Fed index indicates that the first one began in April 1980 and lasted four months. There is slightly more agreement on the dating of the second recession in the early 1980s. Our index indicates that it lasted from May 1981 until January 1983, whereas the Philadelphia Fed index indicates that it lasted from September 1981 until November 1982.

These few similarities aside, our indices and the Philadelphia Fed's disagree sharply on the dates when recessions began and ended (because our indices suggest that recessions last longer). On a very general level however, their indices and ours both identify the same recessions. If the Philadelphia Fed's indices are considered a benchmark, then this rough similarity in dating would still allow us to conclude that our indices adequately capture movement in overall economic activity in both the United States and New York State.

### **III. Forecasting**

Because the coincident index measures the underlying state of the labor market, forecasts of the coincident index (called a "leading index") predict the future course of labor market activity and provide policymakers with an outlook for the future course of variables that depend on the state of the labor market, such as banks' non-current loans and rates of mortgage delinquency.

Because it is constructed from the unemployment rate, non-farm employment and average hours worked in manufacturing, the coincident index is also an excellent predictor of those variables, so we include forecasts of these "key economic variables" in our monthly reports. These forecasts have the added benefit of providing the reader of our reports with a concrete understanding of what the coincident index forecast means.

#### 1. "Terraced" VARs

Our forecasting model consists of a set of "terraces." The top terrace forecasts exogenous variables that are useful in predicting changes in the national coincident index. The forecasts of those exogenous variables are passed down to the next terrace, which forecasts the change in the national coincident index. The national index forecast is then passed down to the next terrace, which forecasts the change in a sub-national index. Finally, at the lowest level, the sub-national index forecast is used to forecast changes in the "key economic variables."

Forecasts on a given terrace are based on autoregressive models, which assume that the change in a given variable depends on past changes in that variable and on past changes in variables at higher level terraces. To be more concrete, this section will explain our forecasting model in terms of a

simple three variable “terraced” vector autoregressive (VAR) model. In practice, there are many more variables in our model, but – to keep the example simple here – these will be discussed in further detail in Section III.4.

The specific example of a terraced VAR that we will use is as follows:

$$\begin{bmatrix} \Delta US_t \\ \Delta NYC_t \\ \Delta unemp_t \end{bmatrix} = \begin{bmatrix} \alpha_{US} & 0 & 0 \\ \beta_{US} & \beta_{NYC} & 0 \\ 0 & \gamma_{NYC} & \gamma_{unemp} \end{bmatrix} \begin{bmatrix} \Delta US_{t-1} \\ \Delta NYC_{t-1} \\ \Delta unemp_{t-1} \end{bmatrix} + \begin{bmatrix} u_{US,t} \\ u_{NYC,t} \\ u_{unemp,t} \end{bmatrix}. \quad (5)$$

The top row of equation 5 (or “top terrace”) models the change in the U.S. coincident index at time  $t$  (denoted:  $\Delta US_t$ ). In this case, it is assumed that  $\Delta US_t$  depends only on the previous value of the change in the US index (i.e.  $\Delta US_{t-1}$ ) and the residual:  $u_{US,t}$ . In such a model, forecasts of the change in the U.S. coincident index will therefore depend exclusively on past values of the change in the US index.

The second row models the change in the New York City coincident index at time  $t$  (denoted:  $\Delta NYC_t$ ). According to equation 5,  $\Delta NYC_t$  depends on  $\Delta US_{t-1}$ , its own past value (i.e.  $\Delta NYC_{t-1}$ ) and the residual:  $u_{NYC,t}$ . Forecasts of the change in the New York City coincident index will therefore depend on past values of the change in the New York City index as well as past values of the change in the U.S. index.

Finally, the third row models the change in the New York City unemployment rate at time  $t$  (denoted:  $\Delta unemp_t$ ). In this case, it is assumed that  $\Delta unemp_t$  depends on  $\Delta NYC_{t-1}$ , its own past value (i.e.  $\Delta unemp_{t-1}$ ) and the residual:  $u_{unemp,t}$ . Forecasts of the change in the New York City unemployment rate will depend on past values of the change in the New York City unemployment rate and past values of the change in the New York City coincident index. It is important to note that forecasts of the change in the New York City unemployment rate will also depend on past values of the change in the U.S. index (because the change in the New York City index depends on past values of the change in the U.S. index).

To set up the terraced VAR, we first created an ordinary VAR using Pfaff’s (2008) “vars” package for R (R Development Core Team, 2008). We then used ordinary least squares (OLS) regression to estimate the coefficients of the terraced VAR and replaced the ordinary VAR coefficients with the coefficients of the terraced VAR.

We also replaced the residuals in the VAR object with the rescaled residuals<sup>6</sup> from the OLS equations, so that the VAR object’s residual covariance matrix could be used to compute the confidence intervals around our forecasts.

## 2. Long-Run Assumptions

As mentioned previously, a terraced VAR models *changes* in the variables of interest. We had to express each model in terms of changes to remove the spurious correlation that arises between two unrelated variables that trend upward (or downward) over time.

We also had to make sure that our terraced VARs do not contain a “unit root,” so that the effect of any given shock will fade over time. (In other words, the model assumes that the events of 20 or 30 years ago do not affect the month-to-month fluctuations in the variables we are examining.)

Because all shocks fade over time and because our terraced VARs do not contain an intercept term, our models implicitly assume that the changes in the coincident index and changes in the key economic variables converge to zero in the long run. Since the changes are zero in the long run, the model assumes that the coincident index and key economic variables remain constant in the long run.

In theory, this implies a prediction that the economy will never recover from the current economic crisis. In practice however, forecasts of exogenous leading economic indicators, such as unfilled orders for durable goods (discussed in Section III.4) act as an implicit intercept, which allow our model to predict both recovery from recession and decline from expansion.

### 3. Confidence Intervals

When forecasting, we must assume that the errors in equation 5 will equal zero. In other words, when forecasting the New York City coincident index we implicitly assume that we know the future course of the US index with certainty. Similarly, when we forecast the New York City unemployment rate we implicitly assume that we know the future course of the New York City index with certainty.

Of course, we do not know those values with certainty. All of our forecasts are prone to error, which we must account for. To that end, we estimate a range of forecast values, within which we can be 90 percent certain that the true values will fall. As mentioned in Section 3.1, these estimates are based on the residuals that we obtained when we estimated the coefficients of the terraced VAR.

To compute the confidence intervals, Pfaff’s “vars” package uses forecast error variance decomposition, which is based on the Wold (1954) moving average decomposition for stable VAR-processes, which is defined as:

$$\mathbf{y}_t = \Phi_0 \mathbf{u}_t + \Phi_1 \mathbf{u}_{t-1} + \Phi_2 \mathbf{u}_{t-2} + \dots, \quad (6)$$

where  $\mathbf{y}_t$  is the vector of dependent variables at time  $t$ ,  $\mathbf{u}_{t-i}$  is the residual vector at time  $t - i$  and the  $\Phi_i$  are matrices of parameters that depend on the coefficients of the VAR (or terraced VAR in our case). If the residuals are interpreted as unforeseen economic shocks, then equation 6 shows that current changes in our model’s variables depend entirely on past shocks.

To compute the values of  $\Phi_i$ , Pfaff’s “vars” package sets  $\Phi_0$  equal to an identity matrix (with the same number of dimensions as the VAR has variables) and recursively computes  $\Phi_s$  as:

$$\Phi_s = \sum_{j=1}^s \Phi_{s-j} A_j \quad \text{for } s = 1, 2, \dots, \quad (7)$$

where  $A_j$  is matrix  $j$  of the  $p$  matrices of VAR coefficients<sup>6</sup> and where  $A_j = 0$  for  $j > p$ . The values of  $\Phi_i$

are then used to compute the forecast error covariance matrix:

$$\text{Cov} \left( \begin{bmatrix} \mathbf{y}_{T+1} - \mathbf{y}_{T+1|T} \\ \vdots \\ \mathbf{y}_{T+h} - \mathbf{y}_{T+h|T} \end{bmatrix} \right) = \begin{bmatrix} I & 0 & \dots & 0 \\ \Phi_1 & I & & 0 \\ \vdots & & \ddots & 0 \\ \Phi_{h-1} & \Phi_{h-2} & \dots & I \end{bmatrix} (\Sigma_u \otimes I_h) \begin{bmatrix} I & \Phi_1^T & \dots & \Phi_{h-1}^T \\ 0 & I & & \Phi_{h-2}^T \\ \vdots & & \ddots & \vdots \\ 0 & 0 & 0 & I \end{bmatrix}, \quad (8)$$

where  $T$  is last period for which data is available,  $h$  is the number of forecast periods,  $I_h$  is an identity matrix with  $h$  dimensions,  $\Sigma_u$  is the residual covariance matrix, the operator  $\otimes$  is the Kronecker product and  $\mathbf{y}_{T+h} - \mathbf{y}_{T+h|T}$  is the difference between the true value of the dependent variable vector at time  $T+h$  and our forecast of it, given the information available to us at time  $T$ .

The square roots of the diagonal elements of the forecast error covariance matrix are the standard errors of the forecasted variables, which we then use to compute the confidence intervals.

Had we estimated the terraced VAR that was used as an example in Section III.1 and then computed the confidence interval around its forecasts, we would find that the confidence interval around the U.S. coincident index is computed as if the New York City variables were not in the terraced VAR at all.

The confidence interval around the New York City index would depend on the variances of the U.S. and New York City index residuals and the covariance between them (i.e. just as if it had come from a standard two-variable VAR), but would be blind to the presence of the New York City unemployment rate in the terraced VAR.

In the third forecast period (and thereafter), the confidence interval around New York City's unemployment rate would depend on all six variances and covariances (just as one would expect from the model).

There are two sources of error, however, that the forecast error variance decomposition cannot account for. One is revisions of the data used to generate the index and forecasts. The other is sampling error. Forecast error variance decomposition does not account for sampling error because it implicitly assumes that the VAR's coefficients are exactly equal to their true values. Had we estimated the coefficients from a different time interval, we would have obtained different coefficient estimates and thus gotten a different forecast.

As Feldstein (1971) has shown, sampling error implies that the forecast error of the New York City variables (in Section III.1) would not be distributed normally. To overcome the problems associated with non-normality, McCullough (1996) proposed bootstrapping.

We have chosen not to use bootstrapped confidence intervals however for two reasons. First, given the complexity of our models, the bootstrapping code is very difficult to write and could introduce an unknown degree of human error into the bootstrapped confidence intervals. Second, the purpose of this exercise is to provide the reader of our reports with a general sense of the direction in which the national, state and local economies are headed and with a basic sense of accuracy. We do not need precise estimates of the distribution of the forecast error.

4. Forecast Accuracy

It is simple to create a terraced VAR and compute the confidence intervals around its forecasts, but there are many possible terraced VAR structures to choose from. Therefore, we need to select the structure that has the most predicative power. In this section, we also wish to show that using coincident indices in our forecasting models increases the model's predicative power.

To that end, we estimated the coefficients of many possible terraced VAR structures using the available data between from 1990 to 2004. We then used the estimated coefficients and the rest of the available data (which ended in December 2008) to create 37 sets of 12-month forecasts and 11 sets of shorter forecasts. Finally, we compared the forecasts to the actual values and computed the Mean Squared Error (MSE) of the model's forecasts:

$$MSE_k = \frac{1}{n} \sum_{i=0}^{n-1} (y_{T+i+k} - y_{T+i+k|T+i})^2 ,$$

where  $k$  is the number of periods ahead for which the variable  $y_t$  is forecasted,  $y_{T+i+k|T+i}$  is the forecasted value of  $y_{T+i+k}$  given the information available at time  $T+i$  and  $n$  is the number of  $k$ -period ahead forecasts.

As Greene (2000) notes, the MSE does not have a scale which allows us to compare the MSE of one forecasted variable to the MSE of another. To get around this problem, we compared the MSE to the variance of the forecasted variable by creating a "relative MSE" statistic, which is similar in spirit to the coefficient of determination:

$$Rel.MSE_k = 1 - \frac{MSE_k}{var(y_{t+k})}$$

where  $var(y_{t+k})$  is the variance of the variable  $y_{t+k}$  in the forecast period.

A relative MSE of one implies perfect prediction, while lower values imply weaker forecasting performance. It is important to note that this statistic may be negative, but – because we cannot know what the variable's mean will be in the forecast period – negativity does not necessarily mean that the forecast is poor. Sometimes, a slightly negative relative MSE is the highest value one can obtain when forecasting a very volatile variable.

Table 1 uses relative MSE to compare our forecast models to both a random walk and an "alternative model," in which the region's coincident index is not used to forecast "key economic variables" (i.e. the unemployment rate, non-farm employment and average hours worked in manufacturing). To keep the table concise, the reported relative MSE statistic is the average of the 12  $Rel.MSE_k$ :

$$Rel.MSE = \frac{1}{12} \sum_{k=1}^{12} Rel.MSE_k$$

Table 1 shows that our forecast models always outperform the “random walk” forecasts (i.e.  $y_{T+k|T} = y_T$  for all  $k$ ). In other words, our forecast models always provide better prediction than simply observing present economic conditions and assuming that the same condition will continue to hold for the foreseeable future.

With three exceptions, Table 1 shows that our forecast models always outperform the forecasts of the “alternative model,” which is the best model that we could develop that does not include the region’s coincident index as an explanatory variable. This shows that the region’s coincident index is a good predictor of the variables that were used to create it.

The three exceptions were the unemployment rates of New York State and the Nassau-Suffolk MSA and non-farm employment of the Putnam-Rockland-Westchester MSA, but in each of these cases, the difference between the forecast model and the alternative model was small. Given the proximity of Nassau-Suffolk and Putnam-Rockland-Westchester to New York City, it may be the case that the labor markets in these two MSAs are more dependent on the state of the New York City economy than they are on their own. Moreover, the fact that New York City accounts for approximately 43 percent of the New York State population, the New York State unemployment rate may also be heavily dependent on the state of the New York City economy.

Interestingly, the coincident indices turned out to be good predictors of themselves. This may be attributable to the auto-regressive processes that the coincident indices follow (i.e. to the “smoothness” of the coincident index series).

The U.S. coincident index also appears to be a good predictor of state and regional coincident indices. This may be attributable to the fact that regional economies are strongly influenced by national economic conditions.

While developing our forecasting models, we also experimented with other variables, such as the Federal Reserve’s measures of industrial production and capacity, the Census Bureau’s series on housing starts, durable goods and retail sales. The model that provided the most predicative power however only included the Census Bureau’s durable goods unfilled orders series as an exogenous variable.

Housing starts, which are often mentioned as a leading indicator, did not prove to be a good predictor of our indices. The lack of correlation may be attributable to the fact that the time period over which we tested our forecast models includes the period during which the housing bubbles in the U.S. and New York State burst. Housing starts were very weak from January 2007 through mid-2009.

In any case, forecast models that included unfilled orders for durable goods proved to be a significantly stronger predictor of our indices than forecast models that included housing starts.

Taken as a whole, one can conclude from the reasonably high values of our forecast models’ relative MSE statistics that our forecasting models capture a good share of the out-of-sample variation in the variables that the models predict.

**Table 1: Forecast Accuracy**

	<i>Forecast Model</i>		<b>Alternative Model</b>		<b>R. Walk</b>
	Rel. MSE	specification	Rel. MSE	specification	Rel. MSE
<b>United States</b>					
Dur. Goods Unfill. Orders	-0.220	DGU(1,2,3,4,5,6)			-0.770
Coincident Index	0.609	DGU(4), US(1,2)			0.494
Unemployment Rate	0.348	US(1,2), UR(1,2)	-0.020	DGU(4), UR(1,2)	-0.320
Nonfarm Employment	0.615	US(1,2), EMP(1,2)	0.390	DGU(4), EMP(1,2)	0.273
Avg. Hours Worked Manuf.	0.080	US(1,2), HR(1,2)	0.001	DGU(4), HR(1,2)	-0.752
<b>New York State</b>					
Coincident Index	0.475	US(1,2), NYS(1,2), NYC(1,2)			0.069
Unemployment Rate	0.368	US(1,2), NYS(1,2), UR(1,2)	0.371	US(1,2), NYC(1,2), UR(1,2)	-0.449
Nonfarm Employment	0.185	NYS(1,2), EMP(1,2)	-0.045	US(1,2), NYC(1,2), EMP(1,2)	-0.640
Avg. Hours Worked Manuf.	0.047	US(1,2), NYS(1,2), NYC(1,2), HR(1,2)	0.028	US(1,2), NYC(1,2), HR(1,2)	-0.895
<b>New York City</b>					
Coincident Index	0.783	US(1,2), NYC(1,2)			0.408
Unemployment Rate	0.259	US(1,2), NYC(1,2), UR(1,2)	0.241	US(1,2), UR(1,2)	-0.703
Nonfarm Employment	0.147	NYC(1,2), EMP(1,2)	-0.234	US(1,2), EMP(1,2)	-0.468
<b>Nassau-Suffolk</b>					
Coincident Index	0.773	US(1,2), NYC(1,2), NS(1,2)			0.419
Unemployment Rate	0.263	US(1,2), NYC(1,2), NS(1,2), UR(1,2)	0.269	US(1,2), NYC(1,2), UR(1,2)	-0.509
Nonfarm Employment	0.166	NYC(1,2), NS(1,2), EMP(1,2)	0.134	US(1,2), NYC(1,2), EMP(1,2)	-0.740
<b>Putnam-R'land-West'r</b>					
Coincident Index	0.661	US(1,2), NYC(1,2), PRW(1,2)			0.479
Unemployment Rate	0.229	PRW(1,2), UR(1,2)	0.216	US(1,2), NYC(1,2), UR(1,2)	-0.537
Nonfarm Employment	0.058	US(1,2), NYC(1,2), PRW(1,2), EMP(1,2)	0.095	US(1,2), NYC(1,2), EMP(1,2)	-1.030

Table continues on the next page

**Table 1 (continued): Forecast Accuracy**

	<b>Forecast Model</b>		<b>Alternative Model</b>		<b>R. Walk</b>
	Rel. MSE	specification	Rel. MSE	specification	Rel. MSE
<b>Buffalo-Niagara Falls</b>					
Coincident Index	0.641	US(1,2), BN(1,2)			0.456
Unemployment Rate	0.254	US(1,2), BN(1,2), UR(1,2)	0.207	US(1,2), UR(1,2)	-0.721
Nonfarm Employment	0.031	BN(1,2), EMP(1,2)	-0.012	US(1,2), NYS(1,2), EMP(1,2)	-1.055
<b>Rochester</b>					
Coincident Index	0.660	US(1,2), Rch(1,2)			0.505
Unemployment Rate	0.292	US(1,2), NYS(1,2), Rch(1,2), UR(1,2)	0.240	US(1,2), NYS(1,2), UR(1,2)	-0.603
Nonfarm Employment	-0.039	NYS(1,2), Rch(1,2), EMP(1,2)	-0.210	US(1,2), EMP(1,2)	-1.168
<b>Albany-Sch.-Troy</b>					
Coincident Index	0.721	US(1,2), NYS(1,2), AST(1,2)			0.496
Unemployment Rate	0.193	US(1,2), NYS(1,2), AST(1,2), UR(1,2)	0.169	US(1,2), NYS(1,2), UR(1,2)	-0.774
Nonfarm Employment	0.124	AST(1,2), EMP(1,2)	0.122	US(1,2), NYS(1,2), EMP(1,2)	-1.030

The numbers in parenthesis are the lag numbers of the variables that appear in the model's equation.

DGU – Durable Goods Unfilled Orders  
 US – United States Coincident Index  
 NYS – New York State Coincident Index  
 NYC – New York City Coincident Index  
 NS – Nassau-Suffolk Coincident Index  
 PRW – Putnam-Rockland-Westchester Coincident Index

BN – Buffalo-Niagara Falls Coincident Index  
 Rch – Rochester Coincident Index  
 AST – Albany-Schenectady-Troy Coincident Index  
 UR – Unemployment Rate  
 HR – Average Hours Worked in Manufacturing  
 EMP – Nonfarm Employment

#### IV. Conclusion and Direction for Future Research

This paper has explained what a coincident index is and has detailed the methodology employed to estimate the values of the coincident index for the United States, New York State and the six largest MSAs in New York State. It has also explained how we use the coincident index to forecast the future course of “key economic variables” in those regions.

No forecast will ever be perfect; however, we account for the inevitable error in our forecasts by using Terraced VARs to simultaneously forecast all of the variables in the model and compute confidence intervals that depend solely on the variables that affect the value of the forecasted variables. The confidence intervals are imperfect because they do not account for sampling error, but these imperfections occur in all VAR model forecast confidence intervals (not just terraced VARs).

As Section III.4 has shown, our forecasts are more accurate than those we could obtain from assuming a random walk and those that we would obtain had we not included the coincident index in our forecasting models.

In future work, we will explore the correlation between our index and other variables of interest. For example, to the extent that borrowers’ ability to meet their monthly mortgage and consumer credit payments depends on the state of their local economy, then we can examine whether there is a correlation between loans past due and the coincident index. We have already found such a correlation in our preliminary work, so we hope to use the forecast of the coincident index to forecast loans past due and predict future delinquency trends.

#### ENDNOTES

1. The coincident index estimates exclude Utica-Rome, Syracuse, Elmira, and Binghamton due to insufficient data.
2. Stock and Watson used data on industrial production, personal income net of transfer payments, hours worked by employees of nonagricultural establishments and total manufacturing and trade sales to develop their index, while Megna and Xu used data on total employment, sales tax revenue (as a proxy for retail sales), hours worked in manufacturing and the unemployment rate.
3. Orr et al. developed their index from data on total employment, real wages and salaries, the unemployment rate and average hours worked in manufacturing.
4. It should be noted, however, that Megna and Xu’s framework used monthly sales tax collection data as a proxy for retail sales instead of a real wage series.
5. We requested, but were unable to obtain, Megna and Xu’s New York State index. Our comparisons with their results are based on their published paper.
6. Rescaling the residuals was necessary to account for the difference in degrees of freedom between the ordinary VAR and the OLS regression.
7. The number of VAR coefficient matrices,  $p$ , is equal to the lag order of the VAR.

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## Using Actual Betting Percentages to Analyze Sportsbook Behavior: The Canadian and Arena Football Leagues

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### ABSTRACT

Sportsbook behavior is tested for the Canadian and Arena Football Leagues using real sportsbook betting percentages from on-line sportsbooks. The balanced book hypothesis of the traditional sportsbook models does not appear to hold for these leagues, as favorites and overs attract more than 50 percent of the betting dollars. Although there is some slight evidence toward shading the line in these directions, there is also no overwhelming evidence supporting the Levitt (2004) hypothesis, as sportsbooks do not appear to be actively pricing to maximize profits. In general, the results seem more consistent with the sportsbook pricing as a forecast, content with earning their commission on losing bets as simple strategies win about 50 percent of the time.

A study by Levitt (2004) in *The Economic Journal* challenged the traditional view of sportsbook behavior. In the Levitt hypothesis, sportsbooks set prices to maximize profits, not to balance the sports betting action. This model differs substantially from the traditional models of sportsbook behavior, such as Pankoff (1968), Zuber, et al. (1985), and Sauer, et al. (1988), where sportsbooks set prices to balance the book. They achieve this by setting a price that attracts equal dollars on each side of the betting proposition. Under this model, using sports betting data to test the efficient markets hypothesis is straightforward. Under the assumptions of the traditional models, the efficient markets hypothesis could be tested with relative ease as the price represents information from all betting participants. Findings that the efficient markets hypothesis could not be rejected, even in a market where investor (bettor) sentiment is likely to run high, served as a measure of support for this theory (e.g. Sauer, et al. 1988).

If sportsbooks are not pricing to balance the book, however, comparisons between sports wagering markets and other financial markets (such as stocks or bonds), particularly in the testing of the efficient markets hypothesis, become suspect. If prices are being set by sportsbooks to maximize profits or are set as a forecast of game outcomes, independent of the flow of betting dollars, prices in these markets are no longer formed by the actions of investors (bettors), but by the sportsbook itself.

One common criticism of the empirical findings of Levitt (2004) is the use of a betting tournament to substantiate the theory, rather than use of actual sportsbook data. The tournament in question used a

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limited number of participants with a fixed entry fee of \$250. The results from this tournament could yield vastly different results from an actual sportsbook, which has a large number of participants who place wagers of varying sizes on the games on which they bet.

In a recent article in the *Journal of Prediction Markets*, Paul and Weinbach (2007) used actual sportsbook data to test Levitt's (2004) hypothesis. Actual percentages of dollars wagered on the favorite and the underdog were obtained for every game of the 2006 NFL season. The results for the pointspread market were consistent with the results of Levitt (2004), as betting did not appear to be balanced, with favorites, in particular road favorites, receiving a greater percentage of the betting volume. In addition, the percentage bet on the favorite became greater as the pointspread on the favorite increased. Simple strategies of betting against the public when the sportsbook was substantially unbalanced (i.e. 70 percent-plus on the favorite) were found to earn positive returns.

Paul and Weinbach (2007) also showed similar results for the totals (over/under) betting market for the NFL as sportsbook.com was found to be unbalanced, with bettors heavily weighted toward the over, which was consistent with the results seen for long samples of total betting in the NFL (Paul and Weinbach, 2002). Similar findings concerning an unbalanced book and bettor preferences for favorites and overs were found in the NBA (Paul and Weinbach, 2008).

This paper explores the wagering market for smaller betting markets, the Canadian Football League and the Arena Football League, employing the same data source used by Paul and Weinbach (2007, 2008). Tests of the traditional model of sportsbook behavior compared to the findings of Levitt (2004) are performed. Regression results illustrating the relationship between the pointspread and the percentage bet on the favorite are shown. Betting simulations are also presented to test if the sportsbook purposefully allows a betting imbalance to maximize profits. In addition, the possibility that the sportsbooks' price is a forecast of the outcome of the game, independent of the actions of bettors, is explored.

## **II. Regression and Betting Simulation Results**

Data from Sports Insights, which provides actual betting information from on-line sportsbooks for the Canadian Football League (CFL) and Arena Football League (AFL), were purchased from their website, [www.sportsinsights.com](http://www.sportsinsights.com). Data were gathered for both the sides (betting on a team against the pointspread) and totals (betting on the total amount of points scored by both teams) markets. Following the method used by Paul and Weinbach for the NFL (2007) and the NBA (2008), we set up a regression to illustrate how the percentage bet on the favorite and the over vary with the magnitude of the pointspread and total and how the existence of a road favorite affects the betting percentages.

A very simple regression model is tested, which illustrates the actions of the sportsbook. The model to be estimated for the sides (pointspread) market is:

$$(\% \text{ Bet on the Favorite})_i = \alpha_0 + \beta_1(\text{Pointspread})_i + \beta_2(\text{Dummy for Road Favorite})_i + \varepsilon_i \quad (1)$$

The dependent variable is the percentage of dollars bet on the favorite. The independent variables include an intercept, the pointspread on the game (presented as a positive number since heavier favorites have larger pointspreads), and a dummy for teams which are road favorites. Road favorites have been shown to be commonly overbet in studies such as Golec and Tomarkin (1991) and Gray and Gray (1997). These studies were cited and used to study the betting tournament data in Levitt (2004). The road favorite dummy variable was found to be positive and significant for the NFL (Paul and Weinbach, 2007) and NBA (Paul and Weinbach, 2008).

A couple of simple propositions can be tested from this regression model. First, if bettors overbet favorites and stronger favorites are bet more heavily than weaker favorites, the coefficient  $\beta_1$  should be positive and significant. If bettors overbet road favorites, the coefficient on the dummy variable,  $\beta_2$ , should also be positive and significant.

The totals market is tested in the same manner as the sides market. The simple regression model for the totals market is:

$$(\% \text{ Bet on the Over})_i = \alpha_0 + \beta_1(\text{Total})_i + \varepsilon_i. \quad (2)$$

If more wagers are accepted on the over as total increases, then  $\beta_1$  should be positive and significant. Market efficiency is tested through the joint null hypothesis that the intercept is zero and the coefficient on the independent variable (either the pointspread or total) is equal to one. The results for the sides (pointspread) regression are presented in tables 1 (2005-2008 CFL) and 2 (2005-2007 AFL). The results for the totals (over/under) regression are presented in tables 3 (2005-2008 CFL) and 4 (2005-2007 AFL).

**Table 1: Pointspread Betting Percentages – Sports Insights 2005-2007 CFL**

Dep. Var: Percent Bet on Favorite	Coefficient	Standard Error	T-Statistic
Constant	59.9959	2.3811	25.1970***
Pointspread	-0.6416	0.3362	-1.9081*
Road Favorite Dummy	1.1337	2.4249	0.4674

\*-notation denotes statistical significance at the following levels - \*-10%, \*\*-5%, and \*\*\*-1%.

**Table 2: Pointspread Betting Percentages – Sports Insights 2005-2008 AFL**

Dep. Var: Percent Bet on Favorite	Coefficient	Standard Error	T-Statistic
Constant	52.2719	1.2928	40.4329***
Pointspread	0.1975	0.1519	1.2409
Road Favorite Dummy	9.0638	1.3446	6.7409***

\*-notation denotes statistical significance at the following levels - \*-10%, \*\*-5%, and \*\*\*-1%.

**Table 3: Totals Betting Percentages – Sports Insights 2005-2007 CFL**

Dep. Var: Percent Bet on Over	Coefficient	Standard Error	T-Statistic
Constant	13.4582	15.7678	0.8535
Total	0.7723	0.3059	2.5251**

\*-notation denotes statistical significance at the following levels - \*-10%, \*\*-5%, and \*\*\*-1%.

**Table 4: Totals Betting Percentages – Sports Insights 2005-2008 AFL**

Dep. Var: Percent Bet on Over	Coefficient	Standard Error	T-Statistic
Constant	24.7974	9.4179	2.6330***
Total	0.2966	0.0893	3.3222***

\*-notation denotes statistical significance at the following levels - \*-10%, \*\*-5%, and \*\*\*-1%.

F-tests were performed for each regression result. The F-test of whether the intercept equaled 50 and the pointspread (total) variable was equal to zero was tested for both pointspreads and totals, while additional F-tests of the intercept equaling 50, the pointspread variable equaling zero, and the road favorite dummy equaling zero were performed for the pointspread regressions. In each case, the null hypothesis could be rejected at the 1 percent level. The F-test results for whether the intercept equaled 50 and the coefficient on the pointspread (total) was zero were found to be (F-values) 47.007 (AFL-Pointspread), 7.5063 (AFL-Totals), 17.571 (CFL-Pointspread), and 6.614 (CFL-Totals).

In tables 1 and 2, the intercept of both the CFL and AFL regression is greater than 50, implying that on the average more than half of the bets accrue to the favorite. The CFL, however, does not look like the NFL, as bigger favorites do not receive an increasing share of the betting dollars, but actually receive slightly less than smaller favorites (significant at the 10 percent level). The road favorite dummy for the CFL is positive, but not statistically significant.

In the AFL, bets on the favorite increase with each additional point of the pointspread, as in the NFL and NBA, but this variable is not found to be statistically significant for the Arena League. The road favorite dummy variable is found to have a positive and significant effect on the amount bet on the favorite. This is similar to the result found in the NFL and NBA, as bettors appear to favor road favorites, which likely reveals a strong preference for the best teams, as it takes a good team to be a road favorite.

Overall, in the sides regressions for the CFL and AFL, some preference for the favorite is found, but the preference for the biggest favorites is not as great as in the NFL and NBA. Road favorites still appear to be popular in the CFL and AFL, although statistical significance is only found for the AFL.

Tables 3 and 4 present the results for the totals (over/under) market. Strong preference for the over was found in the NFL and the NBA (Paul and Weinbach, 2007, 2008) and CFL and AFL bettors appear to have the same preferences. The percentage bet on the over was found to increase with each point of the total. The total was found to have a positive and significant effect on the percentage bet on the over for both regressions.

For comparison purposes, a total of 51 in the CFL (slightly less than the average of 51.31 for the sample) would be expected to generate 52.85 percent of the money on the over. A likely high-scoring game with a posted total of 60 would expect to generate 59.80 percent on the over. In the AFL, a total of 105 (slightly less than the average of 105.21 for the sample) would expect to generate 55.94 percent on the over. A high total of 120 would expect to generate 60.39 percent on the over.

In neither the sides nor the totals does it appear the sportsbook is attempting to set the price to perfectly balance the book. The sportsbook seems content to attract a higher percentage of bets on the favorite and the over without regard to attempting to eliminate its risk by setting the pointspread or total higher to attempt to even the betting action. The sportsbook even seems less concerned when it comes to road favorites and high totals, as the public overbets these propositions and the sportsbook seems content to let them.

Having an unbalanced sportsbook does not necessarily imply that the sportsbook is pricing to maximize profits, as suggested by Levitt (2004). The sportsbook could be setting prices where the public bets on the side of the proposition which loses more often than it wins, earning profits for the sportsbooks, such as in the NFL (Paul and Weinbach, 2007). It could also be setting prices as a forecast, without regard to the betting percentages of the public, as seems to be the case in the NBA (Paul and Weinbach, 2008).

To attempt to determine if sportsbooks earn profits by pricing at a point other than where the book is balanced, simple betting simulations are presented for both the CFL and the AFL. The first simulations attempt to determine if the samples used in this study exhibit similar betting biases to results found in longer samples for the CFL (Paul and Weinbach, 2007) and the AFL (Borghesi, Paul, and Weinbach, 2009). Biases found in these papers illustrate that bettors of these sports prefer the biggest favorites and the highest totals. Results are shown for the CFL, sides and totals, in tables 5 and 6 and for the AFL, sides and totals, in tables 7 and 8.

**Table 5: Simple Pointspread Betting Simulation: Bet the Underdog when Favorite exceeds a certain Pointspread Threshold – CFL (2005-2007)**

Favorite Threshold	Favorite Wins	Underdog Wins	Underdog Win Percentage	Log-Likelihood Ratio Test: Fair Bet	Log-Likelihood Ratio Test: No Profits
10+	10	14	58.3333%	0.6698	0.3431
7+	28	31	52.5424%	0.1526	0.0006
3+	79	84	51.5337%	0.01534	NA
All	92	106	53.5354%	0.9907	0.1060

The log likelihood test statistics have a chi-square distribution with one degree of freedom. Critical Values are 2.706 (for an  $\alpha=0.10$ ), 3.841 (for an  $\alpha=0.05$ ), and 6.635 (for an  $\alpha=0.01$ ). \* is significance at 10%, and \*\* is significance at 5%.

**Table 6: Simple Total Betting Simulation: Bet the Under when Total Exceeds a Certain Threshold – CFL (2005-2007)**

Total Threshold	Over Wins	Under Wins	Under Win Percentage	Log-Likelihood Ratio Test: Fair Bet	Log-Likelihood Ratio Test: No Profits
55+	13	18	58.0645%	0.8100	0.4039
50+	48	67	58.2609%	3.1536*	1.6043
All	77	102	56.9832%	3.5031*	1.5273

The log likelihood test statistics have a chi-square distribution with one degree of freedom. Critical Values are 2.706 (for an  $\alpha=0.10$ ), 3.841 (for an  $\alpha=0.05$ ), and 6.635 (for an  $\alpha=0.01$ ). \* is significance at 10%, and \*\* is significance at 5%.

**Table 7: Simple Pointsread Betting Simulation: Bet the Underdog when Favorite exceeds a certain Pointsread Threshold – AFL (2005-2008)**

Favorite Threshold	Favorite Wins	Underdog Wins	Underdog Win Percentage	Log-Likelihood Ratio Test: Fair Bet	Log-Likelihood Ratio Test: No Profits
10+	37	53	58.8889%	2.8596*	1.5394
7+	85	105	55.2632%	2.1092	0.6347
3+	200	206	50.7389%	0.0887	NA
All	247	260	51.2821%	0.3334	NA

The log likelihood test statistics have a chi-square distribution with one degree of freedom. Critical Values are 2.706 (for an  $\alpha=0.10$ ), 3.841 (for an  $\alpha=0.05$ ), and 6.635 (for an  $\alpha=0.01$ ). \* is significance at 10%, and \*\* is significance at 5%.

**Table 8: Simple Total Betting Simulation: Bet the Under when Total Exceeds a Certain Threshold – AFL (2005-2008)**

Total Threshold	Over Wins	Under Wins	Under Win Percentage	Log-Likelihood Ratio Test: Fair Bet	Log-Likelihood Ratio Test: No Profits
110+	56	83	59.7122%	5.2781**	3.0210*
105+	118	150	55.9701%	3.8300	1.3892
All	252	265	51.2573%	0.3269	0.2611

The log likelihood test statistics have a chi-square distribution with one degree of freedom. Critical Values are 2.706 (for an  $\alpha=0.10$ ), 3.841 (for an  $\alpha=0.05$ ), and 6.635 (for an  $\alpha=0.01$ ). \* is significance at 10%, and \*\* is significance at 5%.

In the CFL, win percentages on simple strategies of bet the underdog or bet the under do win more than 50 percent of the time, but the only statistically significant results are found for the group of all totals and all totals greater than 50. In the AFL, statistical significance is only found at the highest levels (betting the underdog when there are 10+ point favorites and betting the under when the total is 110+). For the subsample of games with the highest totals, a simple strategy of wagering on the under was found to reject the null of no profitability at the 10 percent level.

The biases in this sample are similar to biases seen in longer samples found in Paul and Weinbach (2007) and in Borghesi, Paul, and Weinbach (2009). The biggest favorites and highest totals are priced slightly too high, with contrarian strategies of betting against these publically popular propositions earning large enough profits to reject the null of a fair bet and, in the case of AFL totals, reject the null of no profitability.

To test if sportsbooks are pricing to maximize profits by exploiting common bettor biases, as suggested by Levitt (2004), we test a few simple betting simulations for the CFL and AFL. Given that bettors tend to prefer favorites and overs (in particular, big favorites and high totals), these simulations test the returns to betting against the most popular betting propositions. Given the availability of the betting percentages, when the game is significantly imbalanced (>70 percent, >60 percent, etc.), we test the returns to a contrarian strategy of betting the underdog or under. Given that the sportsbook is weighted on the favorite and over in these situations, these simulations also represent the return the sportsbook earns by not pricing to balance the book.

Returns to these strategies are presented for the CFL in tables 9 and 10, while returns for the AFL are presented in tables 11 and 12. For each situation, the number of favorite wins, underdogs wins, the underdog win percentage, and log-likelihood ratio tests for a fair bet and no profits are presented. The null of a fair bet implies a win percentage of 50 percent, while the null of no profits implies a win percentage of 52.4 percent, the percentage needed to overcome the commission charged by sportsbooks on bets.

**Table 9: Simple Pointsread Betting Simulation: Bet the Opposite of the Public When the Percentage Bet on Favorite Exceeds a Certain Threshold – CFL (2005-2007)**

Percentage Bet on the Favorite	Favorite Wins	Underdog Wins	Underdog Win Percentage	Log-Likelihood Ratio Test: Fair Bet	Log-Likelihood Ratio Test: No Profits
70%+	18	25	58.1395%	1.1446	0.5753
60%+	40	48	54.5455%	0.7283	0.1657
50%+	61	80	56.7376%	2.5681	1.0778

The log likelihood test statistics have a chi-square distribution with one degree of freedom. Critical Values are 2.706 (for an  $\alpha=0.10$ ), 3.841 (for an  $\alpha=0.05$ ), and 6.635 (for an  $\alpha=0.01$ ). \* is significance at 10%, and \*\* is significance at 5%.

**Table 10: Simple Total Betting Simulation: Bet the Opposite of the Public When the Percentage Bet on Under Exceeds a Certain Threshold – CFL (2005-2007)**

Percentage Bet on the Over	Over Wins	Under Wins	Under Win Percentage	Log-Likelihood Ratio Test: Fair Bet	Log-Likelihood Ratio Test: No Profits
70%+	14	16	53.3333%	0.1334	0.0109
60%+	29	39	57.3529%	1.4759	0.6775
50%+	52	64	55.1724%	1.2436	0.3635

**Table 11: Simple Pointspread Betting Simulation: Bet the Opposite of the Public When the Percentage Bet on Favorite Exceeds a Certain Threshold – AFL (2005-2008)**

Percentage Bet on the Favorite	Favorite Wins	Underdog Wins	Favorite Win Percentage	Log-Likelihood Ratio Test: Fair Bet	Log-Likelihood Ratio Test: No Profits
75%+	55	51	51.8868%	0.1510	NA
70%+	125	99	55.8036%	3.0247*	1.0557
65%+	179	172	50.9972%	0.1396	NA

The log likelihood test statistics have a chi-square distribution with one degree of freedom. Critical Values are 2.706 (for an  $\alpha=0.10$ ), 3.841 (for an  $\alpha=0.05$ ), and 6.635 (for an  $\alpha=0.01$ ). \* is significance at 10%, and \*\* is significance at 5%.

**Table 12: Simple Total Betting Simulation: Bet the Opposite of the Public When the Percentage Bet on Under Exceeds a Certain Threshold – AFL (2005-2008)**

Percentage Bet on the Over	Over Wins	Under Wins	Over Win Percentage	Log-Likelihood Ratio Test: Fair Bet	Log-Likelihood Ratio Test: No Profits
75%+	78	68	53.4247%	0.6855	0.0639
70%+	129	131	49.6154%	0.0154	NA
65%+	183	182	50.0137%	0.0027	NA

The win percentages are found to be above 50 percent in most of the sample subsets shown in the tables above for the CFL and AFL. These win percentages, however, are not found to be statistically significant against the null of no profitability. In addition, there is only one subset which is found to be statistically significant against the null of a fair bet, the subset of all AFL games where the public bets 70 percent or more on the favorite, which is significant at the 10 percent level.

Overall, there is some slight evidence that sportsbooks may shade the lines and totals slightly to take advantage of known bettor biases, but this pricing by no means earns substantial profits for the sportsbook. In addition, there is little incentive for informed bettors to take contrarian positions in this market as the returns to these simple betting strategies are not statistically profitable.

It appears sportsbooks generally price the CFL and AFL (set pointspreads and totals) as forecasts with a possible slight shading of the line to the big favorites and high totals. This shading of the pointspreads and totals allows the sportsbook to earn slightly higher profits, but are not large enough to invite informed bettors into the fray. It appears that sportsbooks price these relatively small sports mainly as a forecast, not attempting to perfectly balance the book, and earn their commission on losing bets over time, with win percentages on simple strategies expected to hover around 50 percent.

### III. Conclusions

The betting markets for the Canadian Football League and the Arena Football league were tested in relation to sportsbook pricing behavior using actual betting percentages from real sportsbooks. The results of these tests were compared to previous results found on betting percentages in the NFL (Paul

and Weinbach, 2007) and the NBA (Paul and Weinbach, 2008). Using the betting percentages on each game, we tested these hypotheses for the traditional models of sportsbook behavior, where the book is balanced; the Levitt hypothesis, where sportsbooks price to maximize profits; and a hybrid model where sportsbooks price as a forecast, allowing an unbalanced book, but not exploiting known bettor biases to maximize profits.

In general, the traditional model of sportsbook behavior does not appear to be supported as the betting dollars in the CFL and AFL are not balanced. Favorites and overs tend to attract a higher percentage of the betting action. These results do not necessarily imply that sportsbooks are pricing to exploit known biases and maximize profits, as Levitt (2004) suggests.

To test if sportsbooks price to maximize profits by exploiting known bettor biases, some simple tests were performed on the CFL and AFL data. First, simple betting strategies of betting the underdog and the under were performed. In the CFL, underdogs won slightly more often than favorites, but the results were not found to be statistically significant. In the CFL totals market, for the sample of all totals and the subsample of all totals of 50 or more, the under was found to win often enough to reject the null hypothesis of a fair bet.

In the AFL, big underdogs (10 or more points) were found to win more often than implied by efficiency (nearly 59 percent of the time), while the sample of all underdogs won more than 50 percent of the time, but the results were not statistically significant. In the AFL totals market, the under was found to win nearly 60 percent of the time for games with the highest totals and was found to be significant.

When considering betting percentages and calculating the results when the betting public heavily supports the favorite or over (meaning the sportsbook is an active participant on the side of the underdog or under), little in the way of statistical significance was found. The only case where a fair bet could be rejected was in situations where the public had 70 percent or more on the favorite in an AFL game, where the underdog won more than implied by efficiency. The rest of the results of these tests could not reject the null of a fair bet.

Overall it appears there may be some slight shading of the pointspread and total toward the favorite and the over in the CFL and the AFL. This shading is not great, however, and does not offer much in the way of expected profits for contrarian bettors. Given that the betting action is not found to be balanced, but profitability is not found to a great extent by taking the side of the sportsbook (underdogs and unders), it appears that the sportsbook does not follow the traditional model of sportsbook behavior nor the Levitt hypothesis. It appears that sportsbooks price generally as a forecast, with a slight shade (particularly in obvious cases – big favorites or high totals) toward the more popular side of the proposition. This situation results in findings that are more similar to the NBA (Paul and Weinbach, 2008) than the NFL (Paul and Weinbach, 2007).

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## Credit Union Growth in Mid-sized Markets

**Robert Tokle\* and Joanne Tokle\*\***

The credit union movement in the U.S. began in 1909 (National Credit Union Association, 2010). Credit unions differ from banks in that they are member-owned cooperatives that operate as nonprofits with restricted fields of membership. Since they are nonprofits, they cannot raise capital by issuing stock in financial markets. Rather, all capital comes from retained earnings. In addition, members of the board of directors cannot be paid for their services (Robbins, 2005). Nevertheless, competition of credit unions with banks has been well documented in studies such as Tokle and Tokle (2000), Heinrich and Kashian (2008), and Feinberg (2001).

The financial crisis of 2008-09 has affected financial institutions across the U.S., including credit unions. And, credit unions, like other depository institutions, will face challenges in the years ahead. One challenge facing credit unions will be growth. A recent CEO Advisory Group's study warns of stagnant growth. The study states that "since 2000, 45 percent of all CU's have had a net loss of members, and a shocking 59 percent of all CU's under \$10 million in assets had net losses" (<http://www.ceoadvisory.com/page.php?page=76>, 2008).

Corporate credit unions, which provide services such as check clearing to natural person (consumer) credit unions, have encountered difficulties in the 2008-09 financial crisis, as two of them were placed in conservatorship by the National Credit Union Administration (NCUA) in early 2009. This presents a further challenge to credit unions because actions taken to stabilize the corporate credit unions are being paid for by the natural person credit unions. Thus, NCUA estimates that the net worth ratio of natural person credit unions will be lowered by 65 basis points (American Bankers Association, 2009).

Credit unions grow at different rates for various reasons. While the number of credit unions peaked at 23,866 in 1969, there were just 8,147 credit unions at year-end 2008 (CUNA, 2009). Many of the remaining credit unions have grown larger, and Wilcox (2006) states that "by various measures, larger credit unions have recently had stronger financial performance than smaller credit unions, indicating that these institutions face large and pervasive economies of scale" (p. 1). A number of factors affect credit union growth and performance, and this study in particular examines growth factors beyond credit union size, including the role of capital/asset ratios.

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While consistent with previous studies, this work adds to the literature in a number of ways. Most previous studies of credit union growth used data from the 1990s. This study uses 2002-2004 data from mid-sized cities, in order to be more representative of distinct local markets. In addition, two new independent variables, used vehicle loans rates and loan-to-total asset ratios, were included.

The Literature Review discusses the main findings of credit union growth studies in the U.S. and Europe. Some studies have found that small credit unions grow faster than large ones, while others find the opposite is true. Bank growth studies report mixed results as well.

Our model includes variables used in other growth studies, such as credit union size, previous growth, ratio of loans charged off, operating expense ratio, capital-asset ratio, and the ratio of fee income to total assets. The expected effect of each of these variables is discussed in the Model section of the paper. In addition, the two new independent variables listed above add to our knowledge of factors that influence credit union growth.

The Results section details the effect of various factors on credit union growth. When comparing average growth rates of different size credit unions, large credit unions grew faster than small credit unions. However, the regression results show that once we hold other factors constant, small credit unions grew faster. In other words, differences in growth rates may be explained by characteristics other than size alone.

Like other studies, we found that growth persists; credit unions that grew in the previous time period tended to keep growing. High levels of bad debt hamper growth, as do higher expenses. On the other hand, credit unions with higher proportions of fee income tended to grow faster. The capital-asset ratio was not a significant factor in explaining growth, but this was not surprising in light of results of previous studies.

Of the two variables not previously tested in other studies, the loan-to-asset ratio, as expected, had a positive effect on growth. This suggests that credit unions with tighter liquidity are more aggressive in attracting deposits, which leads to higher growth rates. However, higher used vehicle loan rates were associated with higher growth—an unexpected finding.

The Limitations section discusses potential shortcomings of the study. For example, the quality of a credit union's management team could not be modeled with available data. And, current market conditions are considerably different from those prevailing in 2004, making extrapolation to today's market problematic.

We conclude by noting that although most credit unions are small in size, they have been growing larger due to both credit union growth as well as smaller credit unions merging with larger ones. This trend is likely to continue, especially in light of our current financial market conditions.

## Literature Review

Many studies of firm growth test the hypothesis that firm growth is random. See, for example, the Law of Proportionate Effect, first developed by Gibrat (1931). These studies usually examine whether growth rates are related to firm size, whether growth tends to persist, and whether variability of growth is related to firm size. For credit unions, growth of assets is typically used to measure firm growth, although membership growth is sometimes used. Other variables that may affect credit union growth include age of the firm, bad-debt ratios, efficiency, return on assets and capital-asset ratios.

Recent studies of credit union growth include those by Ward and McKillop (2005), Goddard et al. (2002) and Goddard and Wilson (2005). The studies by Goddard et al. used samples of U.S. credit unions from the 1990s, while Ward and McKillop used a sample of credit unions from the U.K. in the 1990s. In the U.S., large credit unions tended to grow faster than small credit unions, although an earlier study by Barron et al. (1994), which used NYC credit unions from 1914-1990, found that small credit unions tended to grow faster. Ward and McKillop found that in the U.K., small credit unions grew faster. Goddard et al. (2002) emphasized that “although large credit unions grew faster than small ones, they tended to do so for specific reasons: because they were more efficient, or because they had lower capital or bad debt ratios” (p. 2354). These studies also tested whether growth persisted over time. Ward and McKillop (2005) and Goddard and Wilson (2005) found that growth did persist. On the other hand, Goddard et al. (2002) found negative persistence of growth, i.e., “credit unions that achieve above-average growth in one period tend to grow more slowly in the next” (p. 2345).

More recently, Goddard et al. (2008b) used a sample of credit unions from the NCUA data base (1991-2001) to identify sources of variation in financial performance, as measured by growth of membership and assets, using nested analysis of variance. They found that geography, type of common bond and type of charter (federal vs state) effects make only minor contributions to variation in credit union growth; individual credit union effects explain a large portion of variation in growth. These individual effects, which may include staffing decisions and product portfolio choices, are more pronounced for small credit unions than for large ones. Another study by Goddard et al. (2008a) used a sample of U.S. credit unions from a different time period (1993-2004) to examine diversification and financial performance using instrumental variables regression. They found that small credit unions do not have the scale or expertise to benefit from diversification in the way that larger credit unions do. Similarly, Wilcox (2006) reported a widening gap in the financial performance of large and small credit unions from 1980-2004, attributable to the cost advantages of large credit unions and the fact that expanding fields of membership allow consumers to choose among competing institutions.

Stern et al. (2009) used a sample of 490 credit unions with data from the second quarter of 1994 to the first quarter of 2006 to examine factors that affect the growth of credit union liabilities rather than assets. Specifically, they disaggregated deposits into share drafts, regular shares, money market accounts, share certificates, and IRA/Keogh accounts, and included deposit rates as explanatory

variables in explaining growth of these various deposits. They found that the “growth rate of a deposit category is negatively related to interest rates offered on other types of accounts” (p. 259). Share certificate rates had the largest impact on total share growth.

Although not directly addressing growth issues, a couple of studies have examined efficiency of credit unions. Tripp et al. (2004) used NCUA data from 1998-2002 in a linear programming study of efficiency. They found that multiple bond credit unions were more efficient than single bond credit unions. Glass and McKillop (2006) used large credit unions from the NCUA data base (1993-2001) to examine net and gross cost inefficiency. They found increasing returns to scale and limited cost complementarity. Larger credit unions had lower average costs; cost efficiency tended to improve with age.

Since credit unions and banks are both depository institutions, it may be useful to consider some of the results that have been reported in bank growth studies. Recent examples include those of Cyree et al. (2000a), Cyree et al. (2000b), Goddard et al. (2004), and Wilson and Williams (2000). These studies analyzed U.S. banks, with the exception of Wilson and Williams who examined European banks. The studies found mixed results regarding the Law of Proportionate Effect. Banks that did not grow tended to be smaller in the Cyree et al. (2000b) study, while Goddard et al. (2004) and Wilson and Williams (2000) found little evidence of a relationship between size and growth (except in Italy). In addition, banks with lower capital ratios were more likely to grow.

This study adds to the previous studies in a number of ways. While most of the previous credit union growth studies examined time periods from the 1990s, our study uses sample from a more recent time period of 2002-04. Second, the mid-sized cities in the sample were selected to be in rural areas rather than from larger urban areas so that they would be more representative of distinct local markets (Tokle and Tokle, 2008). And, finally, we include used-vehicle loan rates and the loan-to-total asset ratios as two new independent variables in a credit union growth model.

### **Sample**

Credit unions in 25 mid-sized cities in rural areas of the U.S. were selected for study. Credit unions with extremely large growth rates (more than 35 percent) were excluded to avoid using those that merged during the sample period. The cities were not part of larger urban areas so that the municipalities represented distinct local markets. A total of 296 credit unions were included in the sample. During this time period, the number of credit unions fell from 9,688 in 2002 to 9,014 in 2004, while their total assets rose from \$557 billion to \$647 billion (Census Bureau). These trends are expected to continue (Nikolopoulos and Handrinos, 2008). All data were taken from NCUA's individual credit union call reports for June 2004 unless otherwise noted under the descriptions of the variables in the next section.

### The Model

The dependent variable is the credit union's logarithmic growth between 2003 and 2004. Previous studies of credit union growth have used similar measures over various time periods. Goddard and Wilson (2005) used a three-year horizon; Goddard et al. (2002) used a 6-month time frame; and Goddard et al. (2004) used a 1-year change in their study of bank growth. Regression corrected for heteroscedasticity with White standard errors was used to fit the model.

Most studies of credit union growth (for example, Goddard et al 2002; Ward and McKillop 2005) state the relationship between credit union growth and size as follows:

$$\ln S_{i,t} - \ln S_{i,t-1} = \beta_0 + (\beta_1 - 1)\ln S_{i,t-1} + \varepsilon_{i,t}$$

$S_{i,t}$  is credit union size (assets) at time period  $t$  and  $S_{i,t-1}$  is the size in the previous time period;  $\varepsilon$  is a random disturbance.  $\beta_1$  represents the effect of initial size on the credit union's later growth. If  $\beta_1 = 1$ , then the Law of Proportionate Effect holds and firms size does not affect growth; if  $\beta_1 > 1$ , then large firms grow faster than small firms, and if  $\beta_1 < 1$ , then small firms grow faster than large firms. (For a thorough explanation see Ward and McKillop (2005), p. 1835.)

To include previous growth, the equation can be modified to include:

$$\ln S_{i,t} - \ln S_{i,t-1} = \beta_0 + (\beta_1 - 1)\ln S_{i,t-1} + \beta_2(\ln S_{i,t-1} - \ln S_{i,t-2}) + \varepsilon_{i,t}$$

If  $\beta_2 > 0$ , growth trends persist into the next time period.

Additional variables expand the model to include:

$$\ln S_{i,t} - \ln S_{i,t-1} = \beta_0 + (\beta_1 - 1)\ln S_{i,t-1} + \beta_2(\ln S_{i,t-1} - \ln S_{i,t-2}) + \beta_3 X_{3,i,t} + \dots + \beta_8 X_{8,i,t} + \varepsilon_{i,t}$$

The  $X$ 's represent the remaining independent variables. The empirical results of this model are reported in a later section.

One-tailed hypothesis tests of the following variables were used unless otherwise noted.

**Credit Union Size.** The logarithm of the credit union's total assets in 2003 was used to represent size. The Law of Proportionate Effect (Gibrat, 1931) suggests that growth is unrelated to size of the firm. However, some studies of credit union growth have found that large firms tend to grow faster than small firms (Goddard and Wilson, 2005, and Goddard, et al. 2002), while others have found that small credit unions grow faster than large credit unions (Ward and McKillop, 2005, and Barron et al., 1994). This is a two-tailed test.

**Previous growth.** The credit union's logarithmic growth between 2002 and 2003 was used as an explanatory variable to test for the persistence of growth. Ward and McKillop (2005) found that if growth was above average in one period, it tended to be above average the next period. Goddard and Wilson (2005) also found a positive persistence of growth. Some studies of bank growth report the same effect (Goddard et al., 2004 and Wilson and Williams, 2000). However, Goddard et al. (2002) did not find a positive persistence for credit union growth. Therefore, this hypothesis test will be two-tailed.

**Net Charge-offs/Average Loans.** Charge-offs are measured as the total loans charged-off during the previous 12 months divided by total loans. Goddard et al. (2002) reported that high levels of bad debt may indicate a poorly run credit union, with below average growth. Therefore, the sign of this variable's coefficient is hypothesized to be negative.

**Net Operating expenses/average assets.** Goddard et al. (2002) found the highest growth from the most cost efficient credit unions, using a cost-income ratio to capture efficiency. Leggett and Strand (2002) found that as credit unions grow and add members, "benefits are transferred from members to management," so that economies of scale experienced from growth may be offset by agency problems. We use net operating expenses/average loans as a measure of efficiency. A higher expense ratio suggests the credit union is less efficient and hence will experience lower growth; thus, the coefficient of this variable is expected to be negative.

**Net Worth/Total Assets (Capital/asset).** Goddard et al. (2008a) studied factors that influence financial performance of U.S. credit unions. They state that credit unions with a high capital-asset ratio may be operating overcautiously and hence are missing investment opportunities. However, "the cost of insurance against bankruptcy be high for a credit union with a low" ratio (p. 1841). They found that risk-adjusted rate of returns (rate of return divided by its standard deviation) are positively influenced by increases in capital-asset ratios, which is similar to findings for banks. They state that "a higher capital-assets ratio is unambiguously associated with increased risk-adjusted profitability" (p. 1846). Since profitability is necessary for future growth, this would suggest that this variable should have a positive coefficient. However, Goddard et al. (2004) found that banks with high capital-asset ratios tend to grow slowly. Similarly, Cyree et al. (2000b) found that banks with lower capital are more likely to grow. In light of mixed results reported in the studies cited here, this hypothesis test will be two-tailed.

**Used-vehicle loan interest rate.** Stern et al. (2009) found that interest rates on various credit union liabilities do affect growth of those deposits. Here we include the rate on used vehicle loans (an asset) to test its effect on growth in assets. Used vehicle rates were used rather than new vehicle rates because financing for used vehicles occurs in more of a local market than for new vehicles, which are frequently financed through auto manufacturers' finance companies that may provide rates as low as 0 percent. Since credit unions typically do not borrow to finance loans over the longer term, if their loan volume increases, they may offer higher rates on liabilities in order to grow those liabilities so they can fund the loans, which would increase asset size. If a credit union charges higher used-vehicle loan rates, we

would expect to see lower growth and vice versa for lower loan rates. Hence, this coefficient is expected to be negative.

**Total loans/total assets.** Credit unions that have a higher loan-to-asset ratio will experience tighter liquidity and thus need to be more competitive in attracting sources of funds (liabilities). For most credit unions, this source of funds would come from deposits and in particular from certificates of deposit, since their flow is sensitive (very elastic) to the level of interest rates offered. And, a faster growth in liabilities means a faster growth in assets on the other side of the balance sheet. Hence, a positive coefficient is expected.

**Fee Income.** Increasingly, noninterest income (from fees for services) is becoming an important source of revenue for financial institutions. Esho et al. (2005) reported that between 1993 and 2001, transaction fees on loans and deposits of Australian credit unions increased from 2 percent to 8.5 percent of total revenue. They found that “increased reliance on fee income generating activities is associated with increased risk,” and that “credit unions that generated a higher proportion of gross revenues from non-interest income had higher risk and lower returns than those that had relatively small proportions of non-interest income” (p. 279). Here we use the ratio of noninterest income to total assets to capture the effect of fee income on growth. A positive coefficient is expected since we expect increased risk taking to be associated with growth.

## Results

Descriptive statistics for the entire sample are reported in Table 1. Table 2 reports descriptive statistics broken down by size of credit unions, with large defined as more than \$50 million in assets.

**Table 1. Descriptive statistics for whole sample (n = 296)**

Variable	Mean	Standard deviation
Growth (2003-2004)	.031	.076
Previous growth (2002-2003)	.065	.075
Total assets	\$59.6 million	\$217 million
Charge-offs	.615	1.07
Net operating expenses	3.054	1.03
Capital/asset ratio	13.19	4.95
Used vehicle loan rate	.065	.018
Loans/assets	.581	.162
Fee income/assets	.0042	.0041

The average growth for all credit unions in the sample was 3.1 percent between 2003-2004, less than the average previous growth of 6.5 percent between 2002-2003. The typical credit union in this sample had assets of approximately \$60 million. The average capital/asset ratio of 13.19 was relatively high in comparison to the credit union industry as a whole, and the ratio of loans to assets of .581 was relatively low.

**Table 2. Descriptive statistics by credit union size. Large credit unions: ≥\$50 million in assets (n = 67); small credit unions: <\$50 million in assets (n = 229).**

Variable	Mean: large	Mean: small	Std dev: large	Std dev: small
Growth (2003-2004)	.064	.021	.078	.072
Previous growth (2002-2003)	.098	.055	.058	.077
Total assets	\$230 million	\$14.2 million	\$448 million	\$12.8 million
Charge-offs	.504	.648	.307	1.213
Net operating expenses	2.899	3.100	.661	1.113
Capital/asset ratio	10.943	13.854	2.836	5.235
Used vehicle loan rate	.054	.068	.010	.019
Loans/assets	.649	.561	.124	.167
Fee income/assets	.0060	.0037	.0038	.0040

Table 2 shows that growth was much higher for large credit unions (6.4 percent) vs. small credit unions (2.1 percent). However, these credit unions differed in ways other than size which may account for variation in growth. For example, small credit unions had higher charge-offs (.65) than large credit unions (.50), had higher net operating expenses (3.1 vs. 2.9), higher capital/asset ratios (13.9 vs. 10.9), lower loan/asset ratios (.56 vs. .65), and less fee income relative to assets (.004 vs. .006). They also had lower previous growth (5.5 percent) than larger credit unions (9.8 percent).

Regression results, corrected for heteroscedasticity with White Standard Errors, are shown in Table 3. Relevant measures include:  $R^2 = .18$ ; adjusted  $R^2 = .16$ ;  $F = 8.00$ ; p-value of F-test <0.0001.

**Table 3. Regression results, corrected for heteroscedasticity. Dependent variable = logarithmic growth in assets, 2003-2004**

Variable	Coefficient	White Standard Error	p-value*
Intercept	-0.09449	0.06657	0.1569
Size	0.00659	0.00343	0.0557
Previous growth (2002-2003)	0.12602	0.07586	0.0978
Charge-offs	-0.01837	0.00483	0.0002
Net operating expenses	-0.01360	0.00507	0.0077
Capital asset ratio	-0.00070	0.00081	0.3913
Used vehicle loan rate	0.48160	0.20986	0.0225
Loan to asset ratio	0.04428	0.03390	0.1926
Fee income to asset ratio	2.7841	1.07549	0.0101

\*Reported p-values are for two-tailed tests.

The size variable shows that small firms grow faster than large firms, holding other factors constant, since the coefficient is less than one. This effect is statistically significant at the 10 percent level. The difference in growth by size of credit union reported in Table 2, which showed large credit unions growing faster than small ones, does not hold other factors constant that may influence growth. Differences in growth rates may be explained by characteristics other than size alone.

The credit unions in this sample show positive persistence in growth, as the coefficient of previous growth is positive and significant at the 10 percent level. Credit unions that grew in 2002-2003 also tended to grow in 2003-2004. This result has been reported in other studies (Goddard and Wilson, 2005 and Ward and McKillop, 2005).

The coefficient of charge-offs is negative and significant at the 1 percent level, as expected. Goddard et al. (2002) suggested that high levels of bad debt may indicate a poorly run credit union, and that seems to be the case in this sample.

Net operating expenses had a negative and strongly significant coefficient, as expected. This suggests that higher expenses reduce growth. The capital/asset ratio was not significant, which was not surprising in light of the mixed results reported in other studies. Credit unions with high capital/asset ratios may be overcautious, but on the other hand they may be avoiding higher costs associated with taking greater risks.

The used vehicle loan rate was expected to have a negative coefficient, but had a positive and significant coefficient instead. One would expect that credit unions with lower loan rates would make more loans and hence grow more quickly.

The coefficient of the loan-to-asset ratio was positive and significant at the 10 percent level (since this is a one-tailed test, the p-value for a two-tailed is divided by two). This would suggest that the credit unions that have a tighter liquidity due to being more loaned out are more aggressive in attracting deposits, which in turn lead to higher credit union growth rates.

The coefficient of fee income to total assets was positive and significant at the 1 percent level. Credit unions with a higher proportion of noninterest income grew faster than those with a lower proportion of fee income. While this may be associated with increasing risk (Esho et al. 2005), it appears to help promote growth.

### **Limitations**

Factors other than the ones used here may influence how quickly individual credit unions grow, but these characteristics are not easily identified or captured with available data. For instance, the quality of a credit union's management team and their willingness (or unwillingness) to take on risk may influence their institution's performance. Even though these credit unions were all selected from similar sized communities, there may be differences in local markets that may explain some of the variation in growth, although previous studies have not found compelling differences due to local factors (Goddard et al., 2008b). Furthermore, the results of this study may not be extrapolated to current market conditions, as the data cover 2002-2004, before the recession and credit crisis of 2008-09.

## Conclusions

Credit unions are an important part of our financial system. Like banks, credit unions take in deposits and make loans, but unlike banks, they are owned by members, not shareholders. Most credit unions are small in size but smaller credit unions have been merging with larger credit unions, leaving ever larger credit unions in existence. This study examines characteristics of credit unions that lead to higher growth.

Results of this study for the most part agree with previous studies. Once other factors have been held constant, smaller credit unions grow faster than large credit unions. The other characteristics that influence growth, aside from size, include previous growth, charge-offs, net operating expenses, and fee income-to-asset ratios. Credit unions with higher charge-offs tend to grow more slowly, indicating that higher levels of bad debt may be associated with poorly managed institutions. Higher operating expenses also lead to slower growth due to lesser efficiency than credit unions with lower operating expenses. Credit unions with higher fee income-to-asset ratios also tend to grow more quickly, most likely due to their seeking additional sources of funds. Finally, one of the new variables, the loan-to-asset ratio, had a positive, significant effect on growth, suggesting that credit unions that are more loaned out are more aggressive in attracting deposits.

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## Betting on Market Efficiency: A Note

Ladd Kochman\* and Ken Giliam\*

### Abstract

Two mechanical betting rules were applied to games in the National Football League for the 2000-2008 seasons. Wagers of \$11 (to win \$10) on all NFL underdogs produced a net loss of \$717. When bets were limited to visiting underdogs, only \$395 (or \$44 per year) was lost. The results suggest that gambling on the outcome of football games can be a rewarding activity for bettors more interested in action than financial gain.

### Background

The clear consensus of academic writers who have investigated the efficiency of football point spreads is that no betting rule can win regularly. From Pankoff (1968) to Boulier et al. (2006), attempts to outguess the oddsmakers have generally proven futile. Where profits have surfaced [e.g., Vergin and Sosik (1999)], replications [e.g., Gandar et al. (2001)] exposed their short-lived nature. Even consistent losing is improbable since the responsible rule could be reversed for regular profits. However, that promise of downside protection offers an attractive opportunity to those willing to view betting as a recreational activity rather than as a money-making venture.

Informal interviews with sports bettors reveal that financial reward is only one of the motivations behind wagering on sports-related outcomes. Others include the challenge of sifting through data to uncover possibly overrated or underrated teams, the suspense when monitoring final scores, a lively topic of discussion with friends and the sheer thrill of winning a bet. Breaking even thus becomes less of a disappointment than a goal.

To achieve it, bettors must apply a strategy evenly and repeatedly for an extended period of time. While an efficient market would seem to make the selection of one mechanical rule over another an unimportant detail, human nature and history teach that some may be better than others. Behavioral finance suggests that the fear of regret explains why investors are slow to sell losing stocks and quick to buy popular ones. Kochman and Goodwin (2007) hypothesized that if bettors share that fear, they would overbet favorites in sports contests—specifically, National Football League games—and thereby increase the probability of underdogs beating the (inflated) point spread. Not surprisingly, Kochman and Goodwin found a significantly nonrandom wins-to-bets ratio of 51.9 percent for NFL underdogs between 1991 and

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\*Coles College of Business, Kennesaw State University

2004. Other studies touting the success of underdogs against the spread include Kochman and Goodwin (2004), Golec and Tamarkin (1991) and Amoako-Adu et al. (1985).

### Methodology

Unfortunately for bettors hoping to make money, nonrandomness does not equate to profitability. The customary transaction cost of 10 percent to place a bet creates a breakeven rate of 52.4 percent. However, for recreational bettors, the failure to earn a profit would not be a deterrent and should make the rule of wagering on NFL underdogs a fitting one.

Because we are largely betting *on* (as opposed to *against*) market efficiency, we are first hypothesizing that the market for NFL wagers is efficient and second that for participants in that market who are more interested in action than financial gain, betting can be a virtually riskless and costless activity. To test that proposition, we placed imaginary bets on underdogs in the NFL during the 2000-2008 seasons. In keeping with the recreational bent of our bettors, we limited the amount of each wager to \$11 (to win \$10). Steele (2009) furnished the historical point spreads and final scores.

### Results

A total of 4341 games in the NFL between 2000 and 2008 were screened for wins and losses against the spread by teams that entered those contests as the underdog. Although wins (1113) outnumbered losses (1077), the 10-percent transaction fee preempted profit-taking. Risking \$11 to win \$10 on each of the 2190 bets resulted in gains of \$11,130 and losses of \$11,847 for a net loss of \$717—or \$79.67 per season. While losing less than 33 cents per wager seems a justifiable cost for the aforementioned benefits, the strategy of limiting bets of the same magnitude to *visiting* NFL underdogs over the same nine seasons reduced the cost per bet to less than \$0.27<sup>1</sup>. When visiting ‘dogs beat the spread on 758 of 1483 occasions, outflows (\$7975) exceeded inflows (\$7580) by \$395—or \$43.89 per season<sup>2</sup>.

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Table 1  
Outcomes of wagers on NFL underdogs (2000-2008)

<b>Strategy</b>	<b>Wins</b>	<b>Bets</b>	<b>W/B</b>
Bet on all NFL underdogs	1113	2190	50.8%
Bet on away NFL underdogs	758	1483	51.1%

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## Conclusions

In sum, we are advocating a kind of *If you can't beat 'em, join 'em* approach that, unlike mainstream studies, seeks to benefit from an efficient football betting market. It is not, however, the intention of the authors to encourage illegal betting but rather to extend the analogy between betting and investing. Investors have long accepted that capital markets are efficient and that passive investing can be both prudent and profitable. By applying the mechanical rule of betting on visiting underdogs in the NFL, bettors can also profit from a passive approach—albeit in the form of entertainment. Future researchers may want to expand that payoff to passive bettors by limiting wagers to those teams or situations with special or personal appeal.

## ENDNOTES

1. Limiting wagers to home underdogs would have produced a net loss of \$322—or \$0.455 per bet.
2. Increased competition among offshore gambling operators has made lower commissions available. A five-percent spread—vis-à-vis 10-percent—would reduce the net loss to \$32.50 and the cost per bet and per season to \$0.022 and \$3.61, respectively.

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**REFEREES**

1. James Booker
2. Joseph Cheng
3. John Heim
4. Elia Kacapyr
5. Michael McAvoy
6. Rodney Paul
7. Jonathan Schwabish
8. Dona Siregar
9. Richard Vogel
10. Qun Wu
11. David Ring

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The New York State Economics Association  
62<sup>nd</sup> Annual Conference  
Park Center for Business and Sustainable Enterprise  
Ithaca College  
October 16 and 17, 2009

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**Editor,**  
**New York Economic Review**

William O'Dea  
SUNY Oneonta

Friday, October 16

6:00- 7:30 p.m. Reception: Country Inns and Suites of  
Ithaca

Saturday, October 17

7:00- 8:00 a.m. Registration and Continental Breakfast  
8:15- 8:35 a.m. Welcome  
8:45- 10:05 a.m. Concurrent Sessions: Group 1  
10:20-11:40 a.m. Concurrent Sessions: Group 2  
11:55-12:25 a.m. Networking Luncheon  
12:35- 1:35 p.m. Keynote Address  
1:50- 3:10 p.m. Concurrent Sessions: Group 3  
3:25- 4:45 p.m. Concurrent Sessions: Group 4  
5:00- 6:00 p.m. Business Meeting (All are Welcome)

**New York State Economics Association  
Annual Meeting October 16-17, 2009  
Park Center for Business and Sustainable Enterprise  
Ithaca College**

**Saturday, October 17**

**7:00-8:00** Continental Breakfast  
Upper Atrium

**8:15-8:35** Welcome Address: Thomas Rochon, President, Ithaca College  
Room 111

**8:45-10:05** Concurrent Sessions: Group 1

**Session 1-A:** Mergers and Technical Change  
Room 103

Chair: Bill O'Dea  
State University of New York at Oneonta  
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Shuo Chen  
State University of New York at Geneseo  
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An Empirical Study of Open Source Software Projects Developing Internet Technology

Discussant: K. Matthew Wong  
St. Johns University  
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The Determinants of Firms' R&D Activity

Beom Tai Kim, and Bong Joon Yoon  
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Discussant: Shuo Chen  
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The True Cost of Mergers in the Health Care Industry

K. Matthew Wong, and Richard Belloff  
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Discussant: Chun-Pin Hsu  
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**Session 1-B:** Undergraduate Research Session I  
Room 104

Chair: Florence Shu  
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Soccer Economics  
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Discussant: James Booker  
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Health Care

Charlene Brooke Miller  
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Discussant: Elia Kacapyr  
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Asset Prices in Monetary Policy Rules: An Augmented Taylor Rule

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Discussant: Elia Kacapyr  
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Effects of Health Care Levels on Human Development in Vietnam

Quan Le  
Elmira College  
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Discussant: Edouard Maifoua-Koukebene  
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**Session 1-C: Labor Economics  
Room 204**

Chair: Darius Conger  
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Understanding Labor Flows in New York State  
Arindam Mandal  
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Discussant: Della Lee Sue  
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Application of 3-Dimensional Area Charts in Excel to the Unemployment Index  
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Discussant: Wade Thomas  
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Moving Beyond GIS Map Making: An Applied Analysis of Employment in the Buffalo MSA  
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Discussant: Robert Culp  
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**Session 1-E: Tour of the Park Center for Business and Sustainable Enterprise  
Tour begins in Room 202**

**Session 1-D: Forecasting and Econometrics  
Room 206**

Chair: Michael McAvoy  
State University of New York at Oneonta  
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Discounted Third Order Serial Correlation  
Joseph Cheng  
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Discussant: Ayse M. Erdogen  
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Forecasting the State Economy with Terraced VARs and Coincident Indices  
Eric Doviak and Sean MacDonald  
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Sean MacDonald  
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Discussant: Michael McAvoy  
State University of New York at Oneonta  
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Consumer Demand for Durable Goods, Non-durable Goods and Services  
John Heim  
Rensselaer Polytechnic Institute  
heimj@rpi.edu

Discussant: Joseph Cheng  
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10:20-11:40 Concurrent Sessions: Group 2

Session 2-A: Economics Education I  
Room 103

Chair: Wade Thomas  
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Business Ideas for Teachers  
Raymond MacDermott  
Virginia Military Institute  
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Discussant: Patrick Meister  
Ithaca College  
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Performance in the Classroom: Student Characteristics and Choices  
Richard Vogel  
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Discussant: Della Lee Sue  
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Gender Equality in Economics Courses:  
Comparative Advantage, Learning Style, or Testing Bias?

Della Lee Sue  
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Discussant: Raymond MacDermott  
Virginia Military Institute  
macdermottjr@vmi.edu

Session 2-B: Undergraduate Research Session II  
Room 104

Chair: Jeffrey Wagner  
Rochester Institute of Technology  
jeffrey.wagner@rit.edu

Japanese versus American Financial Crises:  
Are There Any Lessons to Learn from the Japanese Experience?  
Arina Shnaider  
State University of New York at Oneonta  
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Discussant: Manimoy Paul  
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Socially Responsible Investing  
Michael Shoniker  
State University of New York at Fredonia  
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Discussant: Florence Shu  
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How Accurate Have Professional Forecasts by the Congressional Budget Office and  
The Council of Economic Advisors to the President Been Since 1977?

Gurpal Singh  
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Discussant: Jeffrey Wagner  
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**Session 2-C: Finance**  
**Room 204**

Chair  
Cynthia Bansak  
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CMO Bundling Techniques  
Robert Culp  
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Discussant:  
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Cumulative Voting and the Tension Between Board and Minority Shareholders  
Aiwu Zhao and Alexander Brehm  
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Optimal Portfolio Selection:  
A Comprehensive Study of Time Varying Copula and EWMA Models  
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Discussant:  
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**Session 2-E: Tour and Demonstration: The Center for Trading and Financial Analysis**  
**Trading Room 105**

Presented by Ithaca College Core Trading Consultants

**Session 2-D: International Trade and Development I**  
**Room 206**

Chair:  
Darius Conger  
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Recent Developments in Southeast Asian Trade and development  
Shaienne Osterreich  
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Discussant: Xu Zhang  
State University of New York at Farmingdale  
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Fecundity and Husband-Wife Age and Education Gaps at First Marriage  
Xu Zhang  
State University of New York at Farmingdale  
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Discussant: Shaienne Osterreich  
Ithaca College  
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Environmental Regulations and Bilateral Manufacturing Trade:  
The Case of OECD Countries  
Ayse Erdogan  
Rochester Institute of Technology  
ayse.erdogan@rit.edu

Discussant: Goswald Hughes  
State University of New York at Morrisville  
goswald@gmail.com

11:55-12:35 Networking Luncheon  
Upper Atrium

12:45-1:25 Keynote Address:  
Room 111  
"Unsolicited Advice for the Obama Administration"  
Robert Frank  
Henrietta Jonhson Louis Professor of Management and Professor of Economics  
Johnson Graduate School of Management  
Cornell University

1:35-2:55 Concurrent Sessions: Group 3

Session 3-A: Panel Discussion: Teaching the New Tools of Monetary Policy  
Room 103

Chair: David Ring  
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Panelists: Richard Dietz  
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Wade Thomas  
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Session 3-B: Panel Discussion: Health Care Policy Reform  
Room 104

Chair: Javier Espinosa  
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Panelists: William O'Dea  
State University of New York at Oneonta  
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Javier Espinosa  
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Diane Dewar  
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**Session 3-C: Productivity, Development, and Growth  
Room 204**

Chair  
Elia Kacapyr  
Ithaca College  
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Productivity and the Density of Human Capital  
Jaison R. Abel, Ishita Dey, and Todd M. Gabe  
Federal Reserve Bank of New York  
jaison.abel@ny.frb.org

Discussant:  
Beom Tai Kim  
State university of New York, Binghamton  
bkim9@binghamton.edu

Gram Udyog to Grameen Bank: Why Small is Beautiful Again  
Goswald Hughes  
State University of New York, Oswego  
goswaldh@gmail.com

Discussant:  
Darius Conger  
Ithaca College  
dconger@ithaca.edu

Financial Crises in the Context of Biophysical Limits to Growth  
Kent Klitgaard  
Wells College  
KentK@wells.edu

Discussant:  
Tavis Barr  
Long Island University  
tavisbarr@gmail.com

The Impact of Fishery and Manufacturing Industries on the Bahamas Economic Growth  
Patrick Hamilton and Edouard B. Mafoua-Koukebene  
State University of New York at Canton  
hamiltonp@canton.edu, and mafouae@canton.edu

Discussant:  
Kpoti Klitsou  
State University of New York at Binghamton  
Kklits1@binghamton.edu

**Session 3-E: Tour and Demonstration: The Center for Trading and Financial Analysis  
Trading Room 105**

Presented by Ithaca College Core Trading Consultants

**Session 3-D: Economics Education II  
Room 206**

Chair:  
Manimoy Paul  
Sienna College  
mpaul@sienna.edu

An In-Class Pricing Game  
Patrick Meister  
Ithaca College  
pmeister@ithaca.edu

Discussant:  
Richard Vogel  
State University of New York at Farmingdale  
richard.vogel@farmingdale.edu

Incorporating Project-Based Service Learning in the Public Finance Course  
James Booker  
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Discussant:  
Eric Doviak  
City University of New York  
eric@doviak.net

3:10-4:30 Concurrent Sessions: Group 4

**Session 4-A: International Trade and Development II  
Room 103**

Chair: Elia Kacapyr  
Ithaca College  
Kacapyr@ithaca.edu

State-Dependent Stock Market Reactions to Foreign Investment Behavior  
Chun-Pin Hsu  
City University of New York  
chsu@gc.cuny.edu

Discussant: Patrick Hamilton  
State University of New York at Canton  
hamiltonp@canton.edu

Selectivity and Output of Household Enterprises in Uganda

Tavis Barr  
Long Island University  
tavisbarr@gmail.com

Discussant: Christopher Lominac  
Rochester Institute of Technology  
bleadsoefootball@yahoo.com

HIV Infection and Condom Use in Sub-Saharan Africa

Kpoti Klitissou and Bong Joon Yoon  
State University of New York at Binghamton  
kklitiss1@binghamton.edu

Discussant: Jaison Abel  
Federal Reserve Bank Of new York  
jaison.abel@ny.frb.org

**Session 4-B: Health Economics  
Room 104**

Chair: Patrick Meister  
Ithaca College  
pmeister@ithaca.edu

Nursing Home Quality: Theory and Evidence  
Feng Qian  
State University of New York at Buffalo  
fengqian@buffalo.edu

Discussant: Javier Espinosa  
Rochester Institute of Technology  
jxegse@rit.edu

Disaster Impact on Economic Structure:

Linkage Disruption and Economic Recovery  
Richard Vogel  
State University of New York at Farmingdale  
richard.vogel@farmingdale.edu

Discussant: Feng Qian  
State University of New York at Buffalo  
fengqian@buffalo.edu

Access to and Quality of Nursing Homes

Richard Deitz and Feng Qian  
Federal Reserve Bank of New York  
richard.deitz@ny.frb.org

Discussant: Atindam Mandal  
Siena College  
amamndal@siena.edu

**Session 4-C: Macroeconomics  
Room 204**

Chair: Cynthia Bansak  
St. Lawrence University  
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Expectations for a Consumer-Led Recovery  
Thomas Kopp  
Siena College  
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Discussant: Marwan El Nasser  
State university of New York at Fredonia  
Marwan.EINasser@fredonia.edu

The Liquidity Trap of 2008-2009 and the Federal Reserve Dilemma  
Marwan El Nasser  
State university of New York at Fredonia  
Marwan.EINasser@fredonia.edu

Discussant: John Heim  
Rensselaer Institute of Technology  
heimj@rpi.edu

Separating Income and Substitution Effects of Exchange Rate Changes  
John Heim  
Rensselaer Institute of Technology  
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Discussant: Xu Zhang  
State University of New York at Farmingdale  
zhangx@farmingdale.edu

**Session 4-E: Tour of the Park Center for Business and Sustainable Enterprise  
Tour begins in Room 202**

**4:45-5:45 NYSEA Business Meeting** All members are encouraged to attend.

**Session 4-D: Natural Resource Economics  
Room 206**

Chair: Robert Culp  
Dalton State College  
RCulp@DaltonState.edu

Robust Control of Wolf-Elk-Hunter Systems  
Juan Cockburn, Ken McLoud, and Jeffrey Wagner  
Rochester Institute of Technology  
jeffrey.wagner@rit.edu

Discussant: Wisdom Akpalu  
State University of New York, Farmingdale  
wisdom.akpalu@economics.gu.se

An Approach to the Management of Orchards Vulnerable to Attack by Invasive Species  
Christopher Lominac  
Rochester Institute of Technology  
bleadsoefootball@yahoo.com

Discussant: Kent Klickgaard  
Wells College  
KentK@wells.edu

Are Less Skillful Fishers More Likely to Fish Illegally?  
Wisdom Akpalu  
State University of New York, Farmingdale  
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Discussant: Jeffrey Wagner  
Rochester Institute of Technology  
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## FALL 2010

### Conference Participants

Name	Affiliation	e-mail
1 Jaison	Abel	Federal Reserve Bank of New York, Buffalo
2 Wisdom	Akpalu	State University of New York, Farmingdale
3 Cynthia	Bansak	St. Lawrence University
4 Tavis	Barr	Long Island University
5 Richard	Belloff	International School of Management
6 James	Booker	Siena College
7 Alexander	Brehm	State University of New York, Potsdam
8 Shuo	Chen	State University of New York, Geneseo
9 Joe	Cheng	Ithaca College
10 Juan	Cockburn	Rochester Institute of Technology
11 Darius	Conger	Ithaca College
12 Robert	Culp	Dalton State College
13 Diane	Dewar	State University of New York, Albany
14 Richard	Deitz	Federal Reserve Bank of New York, Buffalo
15 Ishita	Dey	University of Buffalo
16 Michelle	Dolojan	State University of New York, Oneonta
17 Eric	Doviak	City University of New York
18 Marwan	El Nasser	State University of New York, Fredonia
19 Javier	Espinosa	Rochester Institute of Technology
20 Ayse	Erdogan	Rochester Institute of Technology
21 Maryann	Fogarty DiLiberto	Bloomfield College
22 Robert	Frank	Cornell University
23 Todd	Gabe	University of Maine
24 Patrick	Hamilton	State University of New York at Canton
25 John	Heim	Rensselaer Polytechnic Institute
26 Chunpin	Hsu	City University of New York
27 Chin-Wen	Huang	Edinboro University of Pennsylvania
28 Goswald	Hughes	State University of New York, Morrisville
29 Elia	Kacapyr	Ithaca College
30 Beom Tai	Kim	State university of New York, Binghamton
31 Kpoti	Kitissou	State University of New York, Binghamton
32 Kent	Klitgaard	Wells College
33 William	Kolberg	Ithaca College
34 Thomas	Kopp	Siena College
35 Quan	Le	Elmira College
36 Christopher	Lominac	Rochester Institute of Technology
37 Ray	Mac Dermott	Virginia Military Institute
38 Michael	McAvoy	State University of New York, Oneonta
39 Sean	MacDonald	New York City College of Technology
40 Edouard B.	Mafoua-Koukebene	SUNY Canton
41 Arindam	Mandal	Siena College
42 Ken	McCloud	Rochester Institute of Technology
43 Patrick	Meister	Ithaca College
44 Charlene	Miller	State University of New York, Fredonia
45 Frank	Musgrave	Ithaca College
46 William	O'Dea	State University of New York, Oneonta
47 Sean	Ogden	Rochester Institute of Technology
48 Shaianne	Osterreich	Ithaca College
49 Peter	Pasqualino	Fulton-Montgomery Community College
50 Manimoy	Paul	Siena College
51 John	Piccione	Siena College
52 Feng	Qian	University of Buffalo
53 Burton	Relethford	State University of New York, Oneonta
54 David	Ring	State University of New York, Oneonta
55 Craig	Rogers	Canisius College
56 Arina	Shnaider	State University of New York, Oneonta
57 Michael	Shoniker	State University of New York, Fredonia
58 Florence	Shu	State University of New York, Potsdam
59 Gurpal	Singh	State University of New York, Fredonia
60 Leonie	Stone	State University of New York, Geneseo
61 Della Lee	Sue	Marist College
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63 Richard	Vogel	State University of New York, Farmingdale
64 Jeffrey	Wagner	Rochester Institute of Technology
65 Matthew	Wong	St. John's University
66 Bong Joon	Yoon	State University of New York, Binghamton
67 Xu	Zhang	State University of New York, Farmingdale
68 Aiwu	Zhao	Skidmore College

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FRIDAY AND SATURDAY

SEPTEMBER 24-25, 2010

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