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Contextualizing Time

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Introduction

Economic data can be gathered in a variety of forms, depending on the purpose of the analysis. Very often, data come as a "time series": a set of observations drawn on the same variable of interest at a number of points, which are often evenly spaced in time.[2] When more than one economic variable is being examined, the researcher must decide how best to illustrate the relationship between the different time series. The simplest solution is to plot the data in an absolute reference frame. While this approach has intuitive appeal, it can mask important underlying causal relationships among the variables. Alternatively, it is possible to display time series data in a relative time frame, plotting each series relative to an event specific to the individual variable under examination. To the extent that these events explain the behavior of interest, the relative time frame can unmask otherwise hidden relationships.

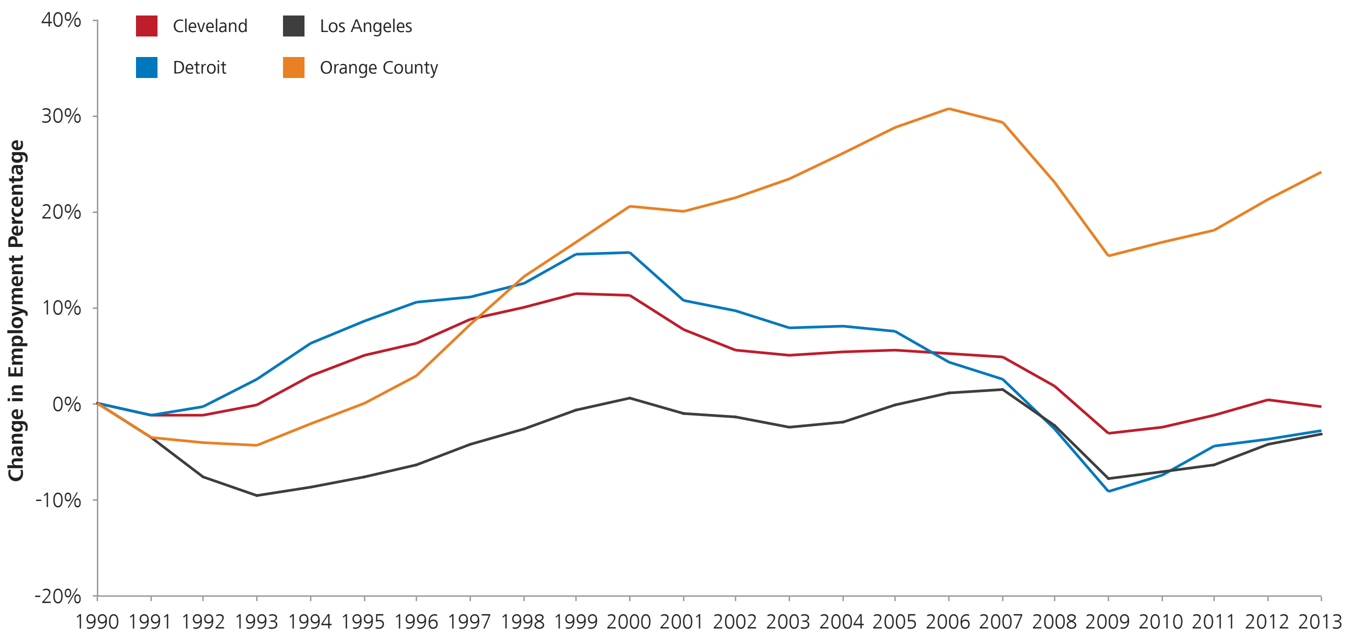
The process of plotting individual time series relative to series-specific events is an established concept.[3] This technique is often employed as an illustrative tool when examining macroeconomic variables—such as GDP, unemployment levels, or changes in consumer durables—in relation to a specific part of the business cycle (*e.g.*, the peak, the recession, or the expansion).[4] Although its usage is widespread in the field of macroeconomics, the concept of relative time frames is less commonly applied in microeconomics. Nevertheless, certain microeconomic analyses can also benefit from contextualizing time based on causal factors.

In this paper, we explore the advantages of series-specific time frames using two real world examples. We introduce and motivate the concept with the familiar macroeconomic comparison of employment data from four US urban centers. The second and central example deals with microeconomic data. There, we consider how a lender's continued participation in the manufactured housing industry affected the level of loss severity on that lender's defaulted contracts.

Macroeconomics: An Example Using Employment Growth Comparisons

A simple example arises when comparing employment growth differences between cities over time.[5] As part of the April 2014 UCLA Anderson Forecast Conference, Dr. William Yu presented data comparing employment levels among cities between 1990 and 2013.[6] Chart 1 shows the percentage change in non-farm employment for each metropolitan area relative to 1990. Without referring to the economic conditions at the time, the level of job generation in Los Angeles (denoted by the black line) at the end of 2013 had changed by no more than that of Detroit (denoted by the blue line) over the same period. That is, at the end of 2013, employment levels in both cities were roughly 3 percent lower than in 1990, 23 years earlier.

Chart 1. **Employment Growth Relative to 1990 Levels Cleveland, Detroit, Los Angeles, and Orange County Annually 1990 to 2013**



Source: William Yu: Problems And Solutions For Los Angeles' Economy, UCLA, April 2014, Figure 2

Although the comparison is chronologically correct, it is likely to be contextually spurious because the macroeconomic engine driving the overall US economy does not uniformly drive the economies of individual metropolitan areas. Therefore, when comparing relative employment generating capabilities, it is generally important to carry out the measurement relative to each area's own employment cycle rather than choosing an absolute reference frame, and hence a measurement with a single starting point in time.

Background

The US recession of 1990 and 1991 is largely attributed to spikes in petroleum prices due to Iraq's invasion of Kuwait in August 1990. For Cleveland and Detroit (denoted by the red and blue lines on both charts), where manufacturing of automobiles and trucks is very important, the recession ended in 1991 as petroleum prices retreated to pre-invasion levels. For Los Angeles and Orange County, California (denoted by the black and orange lines), however, the fall of the Berlin Wall in 1989 added another even more important event: the end of the Cold War, which devastated defense related manufacturing in Southern California.

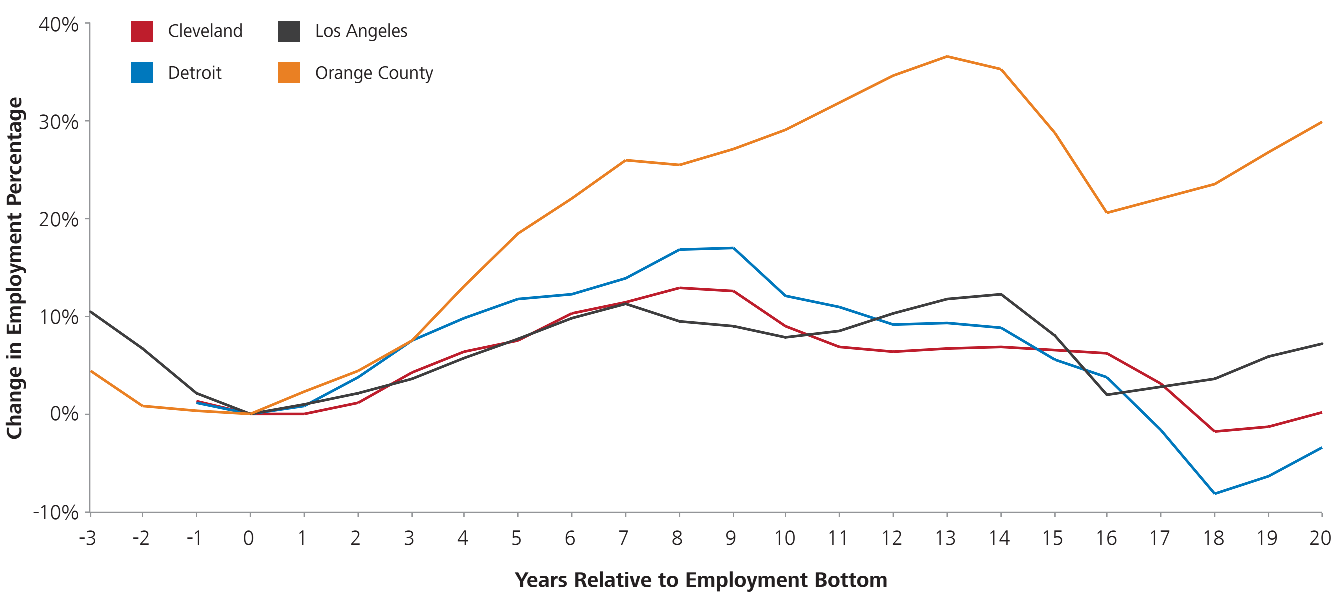
Analysis

For certain comparisons of the job creation capabilities of these four cities since the beginning of the 1990s, it will be important to use a contextual start date rather than a chronological one. The contextual start date sets *time 0* as the year in which each city recorded its lowest annual level of employment ("employment bottom"). Negative units of time denote periods before the employment bottom; positive values denote periods subsequent to the employment bottom.

Chart 2 displays the four cities' employment data[7] on an event scale depicting employment recovery relative to each city's 1990–91 employment bottom. For the US as a whole, the 1990 recession started in July of that year and extended into 1991. Dr. Yu's data indicate that for Detroit and Cleveland, employment bottomed in 1991: denoted by *time 0* on the horizontal axis.

Employment in Los Angeles and Orange County, however, did not bottom out until 1993, due to the negative employment impacts of both the oil price spike and (more importantly) the severe retrenchment of Los Angeles and Orange County's defense industries.

Chart 2. **Employment Growth Relative to 1990–1991 Recession Lows Cleveland, Detroit, Los Angeles, and Orange County**



Source: William Yu: Problems And Solutions For Los Angeles' Economy, UCLA, April 2014, Figure 2

The horizontal level labeled 0% in Chart 2 indicates the employment bottoms for all four cities. Chronologically, these occur at different times for different city pairs under examination: 1991 for Detroit and Cleveland versus 1993 for Los Angeles and Orange County.

Conclusions

Looking at the same data in the context of the disparate regional causes of the 1990–91 recessions for each of the four cities shows different employment growth trajectories from those in Chart 1 for three of the four cities. Our interpretation of the relative time frame analysis is that over the two decades following the employment bottoms of the 1990–91 recession, the economic engine of Los Angeles created better employment growth than those of Detroit and Cleveland, but worse than that of Orange County.

The results for Los Angeles as presented in Chart 2 show a 7 percentage point increase. This is more than a 10 percent swing when contrasted to the 3 percent decline, as presented in Chart 1, for which the data were examined chronologically as opposed to contextually (*i.e.*, relative to the employment bottom). In the case of Orange County, there is a 6 percentage point swing: a 30 percent contextual improvement versus 24 percent when measured chronologically.

Contextually, Detroit and Cleveland showed little difference whether measured in absolute (chronological) or relative (contextual) time frames.[8] Detroit's employment declined roughly 3 percent in both, while Cleveland's employment was relatively unchanged in both.

While contextualized time frames allow the researcher to analyze time series data relative to events that may not have occurred simultaneously (such as the employment bottoms in Southern California and the Midwest), it is important that one has identified the economic forces at work—in this case the labor economy of Los Angeles as compared to those of other cities and the US macro-economy as a whole. Otherwise, it is possible that observed increases or decreases in time series could be due, in part or in full, to a phenomenon called "regression towards the mean."[9] Indeed, if one synchronizes two random, mean-reverting time series relative to their minima, the one with the lower minimum is more likely to show a more substantial increase immediately after *time 0*.

In the case of the employment data, discussed above, there are compelling macroeconomic explanations that underpin the use and interpretation of contextualized time frames. Without a firm theoretical basis, however, relative time frames can bias an analysis that compares time series with abnormally high or low levels at *time 0*.

Microeconomics: An Example Using Loan Loss Severity Rates

A more complex example arose in litigation concerning alleged misrepresentations as to the collateral underling a specific asset-backed security ("the subject security") originated in 1999 by a single lender. Plaintiffs alleged that the loan loss severities[10] in the subject security were due to factual misrepresentations in the offering documents. Specifically, NERA was asked to determine how the loss severities associated with the loan collateral in the subject security compared with those of similar loan pools between 2000 and 2004 ("the subject period").

Background

Collateral for both the subject and benchmark securities are loans made for the purchase of manufactured homes. These residential dwellings are typically sold by dealers and financed with loans similar to those used to purchase automobiles. Manufactured housing contracts are typically fixed-rate and fully amortizing, but with shorter stated maturities—typically 15 to 25 years—than conventional fixed-rate mortgages on site-built dwellings. Note-rates (the interest rate paid by the borrower to the lender) are generally higher on manufactured housing contracts than mortgages with the same number of monthly payments due to the nature of the collateral and demographics of the borrowers.[11]

Unlike conventional site-built homes for which land appreciation often outstrips building depreciation in determining re-sale value, manufactured housing units depreciate over time. This feature contributes to higher severity rates on defaulted contracts compared to mortgages for site built dwellings of the same contractual length. Furthermore, because depreciation is highest during the first years of a manufactured housing unit's use, the borrower is unlikely to have positive equity for many years—typically until the depreciated value of the manufactured housing unit exceeds the amortized principal value of the outstanding contract. During that "negative equity" period—typically seven to eight years—the loss to the lender upon repossession is higher than if the borrower had positive equity in the manufactured housing unit.

By late 1999, as interest rates started to rise while income and job growth slowed, many manufactured housing borrowers struggled and ultimately defaulted on their contracts. Rising defaults in the manufactured housing market led to an increase in the number of repossessions. These events coincided with exits and/or bankruptcies of large retail lenders, thereby increasing the supply of repossessed units in the wholesale market.

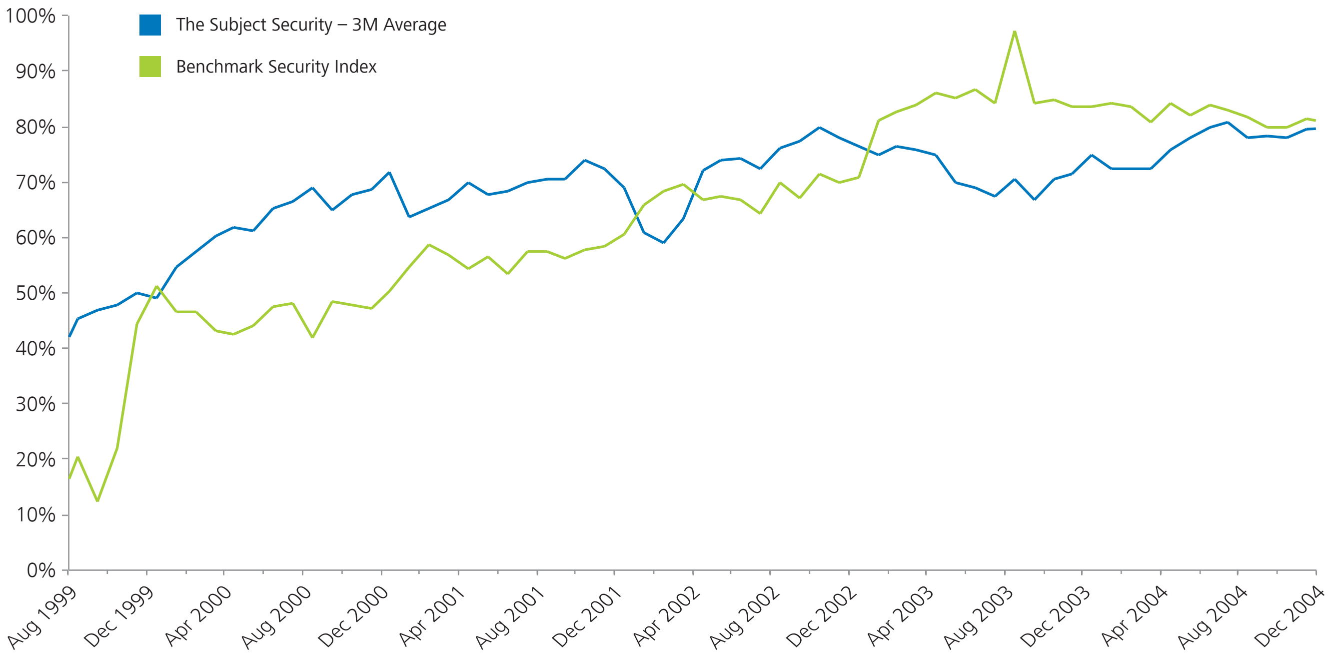
Most importantly, the exit of the large lenders also meant that manufactured housing retail buyers had far fewer—and more costly—financing options, compared to those of the mid-1990s. As discussed below, this reduction in financing availability increased loss severities on manufactured housing contracts both in the collateral of the subject securities as well as the benchmark.

Analysis

To assess the relative loss severity recorded for the subject manufactured housing security, we compared the subject security's loan loss severity to an industry benchmark index, which is composed of loan loss severities of securities issued by several peer originators/lenders. The manufactured housing collateral for both the subject and benchmark securities was originated in 1998–1999.

Chart 3 displays the loss severities for the subject security (denoted by the blue line) and the benchmark (denoted by the green line) chronologically by month from August 1999 to December 2004. For 25 out of the 29 months between the start of the subject period and December 2002, the blue line lies above the green line, indicating that the loss severity rates were higher for the subject security than for the benchmark.[12] However, the green line lies above the blue line for the remainder of the subject period, showing the opposite to be true for 2003 and 2004.

Chart 3. **Severity of Subject Security vs. JP Morgan Index of Peers**
August 1999 through December 2004



Notes and Sources:
Data on the Subject Security are the sum loss of all defaulted loans in a given month and the two previous months, divided by the total balance amounts for the same period. This represents the severity conditional upon repossession.

Benchmark Security Index data represent severity conditional upon default. The index is calculated as a weighted average of deals for a given vintage across a set of several Manufactured Housing issuers from 1999.

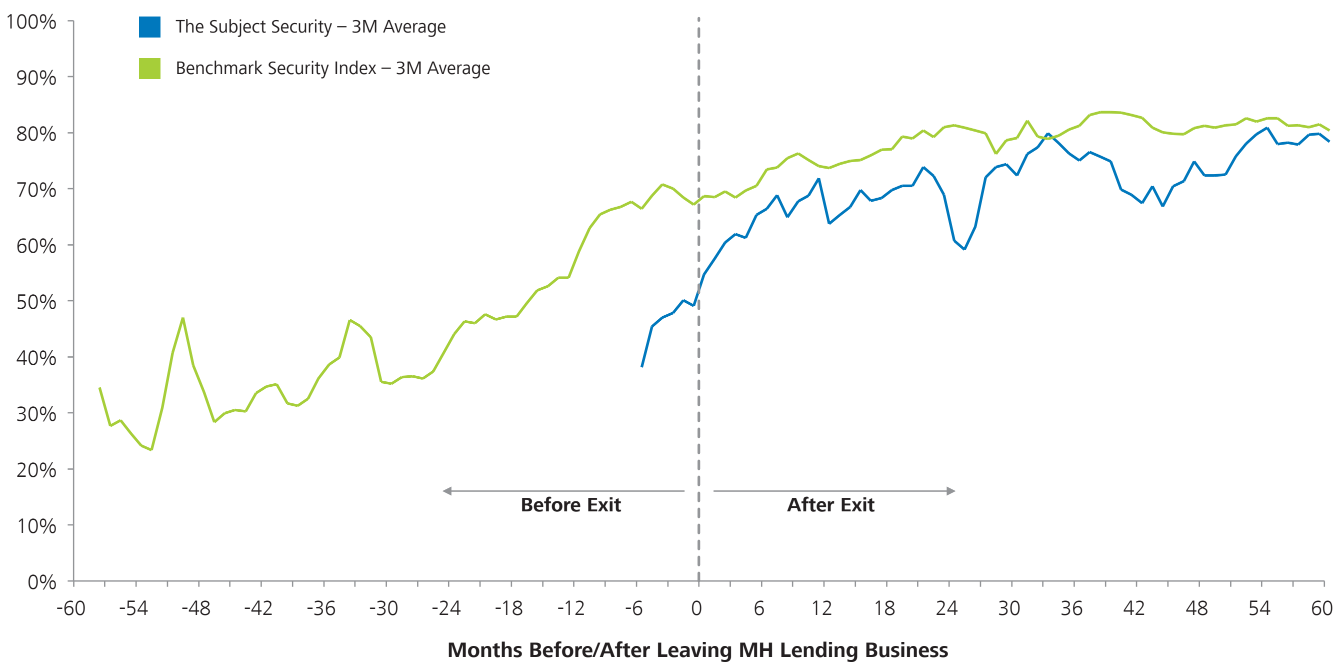
Those comparisons, however, ignore a critical contextual issue: financing availability for manufactured housing units. In other words, the relevant comparison of loss severity for this analysis can be made only when comparable financing is available. For the purpose of this analysis, the availability of comparable financing required the originator to have remained in the business of lending against manufactured housing collateral.

In Chart 4, we have adjusted the individual time scale of the measurements to reflect the dates at which lending companies exited the origination/lending business. Although this adjustment is straightforward for the subject security, a new benchmark index had to be constructed using available data. The peer exit dates and the monthly loss severities were available for ten peers that originated manufactured housing loans in 1998 and 1999. In order to construct a contextual time series, the severity rate for the benchmark relative to time of exiting manufactured housing lending was then constructed by re-aggregating the individual lender data, lining up exit times at a common *time 0*.

For each individual “Months Before/After Leaving Industry,” the severities of the peers were averaged. If, for a particular lender, severity data was unavailable for a given month, that lender was excluded from the calculation. Once this data series was calculated, a three-month moving average of the severity for a given “Months Before/After Leaving Industry” and the composite severity for the previous two months was plotted against the three-month moving average of the subject security.

Time 0 on the horizontal axis of Chart 4 marks the month that all lenders under consideration exited the manufactured housing lending business. In the case of the subject lender, this point in time is chronologically December 1999; however, it represents an array of different months for the lenders whose loans collateralize the benchmark.

Chart 4. **3 Month Average Severity Subject Security vs. Benchmark Security**
By Months Before/After Leaving Manufactured Housing Lending Business



Notes and Sources:
"Months Before/After Leaving Industry" represents the number of months from the time a given issuer ceased making manufactured housing loans. The month an issuer exited the manufactured housing lending business was determined by examining contemporaneous news.

Data on the Subject Security are the sum loss of all defaulted loans in a given month and the two previous months, divided by the total balance amounts for the same period. This represents the severity conditional upon repossession. These data are provided by the issuer of the Subject Security.

Peer index severity was constructed by averaging monthly severity across a set of manufactured housing issuers for a given "Months Before/After Leaving Industry." If an issuer had no severity for a given month, it was removed from the calculation. The average severity of a given "Month Before/After Leaving Industry" and the previous two months is plotted.

Conclusion

Based on the contextualized time series data in Chart 4, we concluded that the subject security's loan loss severity was consistently lower than that of the benchmark security at the time when the subject lender was lending against manufactured housing collateral. This is made evident by the green line, which lies above the blue line for months –8 to 0. These severities remain lower, but converge to levels consistent with severities of the benchmark for the period when lenders had exited the manufactured housing lending market (as shown by the blue line, which lies below—but near—the green line for months 1 to 60, excluding month 33).

Discussion

As is well understood in the field of macroeconomics, an important step for certain comparisons of time series data is the investigation of the context in which individual data series were generated. A pure statistical analysis may reveal particular contextual features of time series, such as graph-specific maxima or minima. On its own, however, such an analysis would neither provide insight into the causal mechanisms that give rise to these features, nor would it explain the relationships between them. Rather, an exploration of the events that coincided with and produced the data is needed. When these events are coupled with knowledge of the economics underlying both the data levels and trends, contextual differences may become clear.

As a motivating macroeconomic example, we examined employment data. By synchronizing the time series according to respective recessions in the four cities, it was revealed that two of the cities experienced substantial increases in employment that were less obvious when viewed in an absolute framework. This example shows that there are circumstances in which valid conclusions regarding time series data are sometimes possible only if one is able to determine the extent to which news and events correspond to each other in absolute time.

This concept also holds true in microeconomic analyses. By lining up the manufactured housing data according to when lenders exited the business, we revealed that (conditional on the financing environment) the subject securities had severities consistently lower than the benchmark—a feature that was not evident in the absolute framework.

As with all analytic tools, relative time frame analysis must be used with care in order to avoid spurious conclusions that could derive from regression towards the mean. A proper understanding of the underlying economics is essential to the interpretation of both absolute and relative time frame analysis.

While there is no strict rule as to whether one should adopt a relative or an absolute framework for the examination of time series data, these examples should motivate the researcher to explore the underlying economics—macro or micro—specific to individual variables under examination and carry out the more suitable analysis on a case-by-case basis.

Notes

[1] Initial loan severity data analysis was carried out by former NERA researcher Felix Turton.

[2] William H. Greene, *Econometric Analysis*, MacMillan Publishing Company, New York, 1990, p. 91.

[3] An example of such a series-specific event is an individual's birthday. When time series are plotted relative to age, date of birth is the logical start date that gives proper contextualization to the time series.

[4] Throughout his textbook *Macroeconomic Patterns and Stories* (Springer, 2009), Edward Leamer provides numerous analyses in which he plots multiple series relative to a temporal origin that is graph-specific. See, for example, p. 115, where the change in unemployment during a given period is plotted relative to the peak of the business cycle of that particular period.

[5] In the example which follows, the cities identified are actually Standard Metropolitan Statistical Areas (SMSAs) as defined by the US Census Bureau. The Census Bureau defines Los Angeles and Orange County as two subdivisions of the same SMSA; they are considered independent of each other for this analysis.

[6] Dr. Yu compared many cities. However, we have taken a subsample to simplify employment growth comparisons.

[7] The data are from Dr. William Yu's article Problems and Solutions for Los Angeles' Economy (Figure 2), UCLA Anderson Forecast April 2014.

[8] Because the time shift was smaller between the chronological and contextual comparisons, it is not surprising that employment growth differences were also smaller for Detroit and Cleveland. Detroit's employment declined roughly 3 percent in both analyses, while Cleveland's was roughly unchanged.

[9] See, for example, *A Guide to Econometrics*, Peter Kennedy, 5th edition, The MIT Press, Cambridge MA, 2003, p. 411.

[10] Loss severity is defined to be (1) the total loss incurred on a loan (or subset of loans) for which the underlying collateral has been repossessed, divided by (2) the unpaid principal balance of the loan. Expressed as a percentage, severity value generally ranges between 0% and 100%. Loss severity is a measure of the extent to which the lender recovers defaulted principal through the sale of the underlying collateral: 0% implying that the lender recovers all principal; and 100% implying that no principal is recovered.

[11] Since 1987, many manufactured housing contracts have been securitized and sold to investors, thereby expanding the sources of financing to prospective manufactured housing buyers. Total issuance of securities backed by manufactured housing contracts was about $100 billion through mid-2010.

[12] The severity of the benchmark exceeded that of the Subject Security for December 1999 and the first quarter of 2002.

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