Estimating Labor and Fiscal Impacts using Louisiana Community Impact Model: Comparing Panel Model and Three Stage Least Squares (3SLS)

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Introduction and Background Information:

Community Policy Analysis System (COMPAS) model is an effective tool to measure the labor and fiscal impacts of different industries in a region. The model exhibits inter-sectoral linkages, since an exogenous shock in any sector of the economy leads to series of changes in other sectors. Community Policy Models such as Louisiana Community Impact Model (LCIM) (Fannin et al, 2008; Adhikari and Fannin, 2010) have been helpful in addressing economic impact questions to address the policy issues of a region. Other policy analysis models such as The Virginia Impact Projection (VIP) Model developed by Johnson (1991), The Iowa Economic/Fiscal Impact Modeling System developed by Swenson and Otto (2000), and an Integrated Economic Impact and Simulation Model for Wisconsin Counties (Shields, 1998), demonstrate how such a model could be used to aid local decision makers. This paper focuses in extending the results from the Adhikari and Fannin, 2010, using panel models and comparing to 3SLS modeling to measure the forecasting performances of estimators.

The COMPAS modeling framework can be applied across the country to address labor market and fiscal impacts from initial changes in economic activity (Johnson, Otto and Deller 2006). At its foundation, COMPAS is an employment driven model. Employment demand is generated by changes in local product demand. The definition of employment demand may vary but the exogenous shock that appears from the changes in employment demand is the basis of the modeling system in COMPAS based models. In many cases, this product is converted to employment demand through the use of input-output models. The input-output (I/O) model is a case where the final demand is exogenous and the labor market supply is perfectly elastic to meet the labor demands generated by the product demands (Beaumont, 1990). In this I/O framework, an exogenous change in demand for the product and services interact with the rest of the economy through linkages of industrial material goods and services in an economy, its local labor market, and ultimately, its fiscal sector. See Figure 1 for an example of this structure.

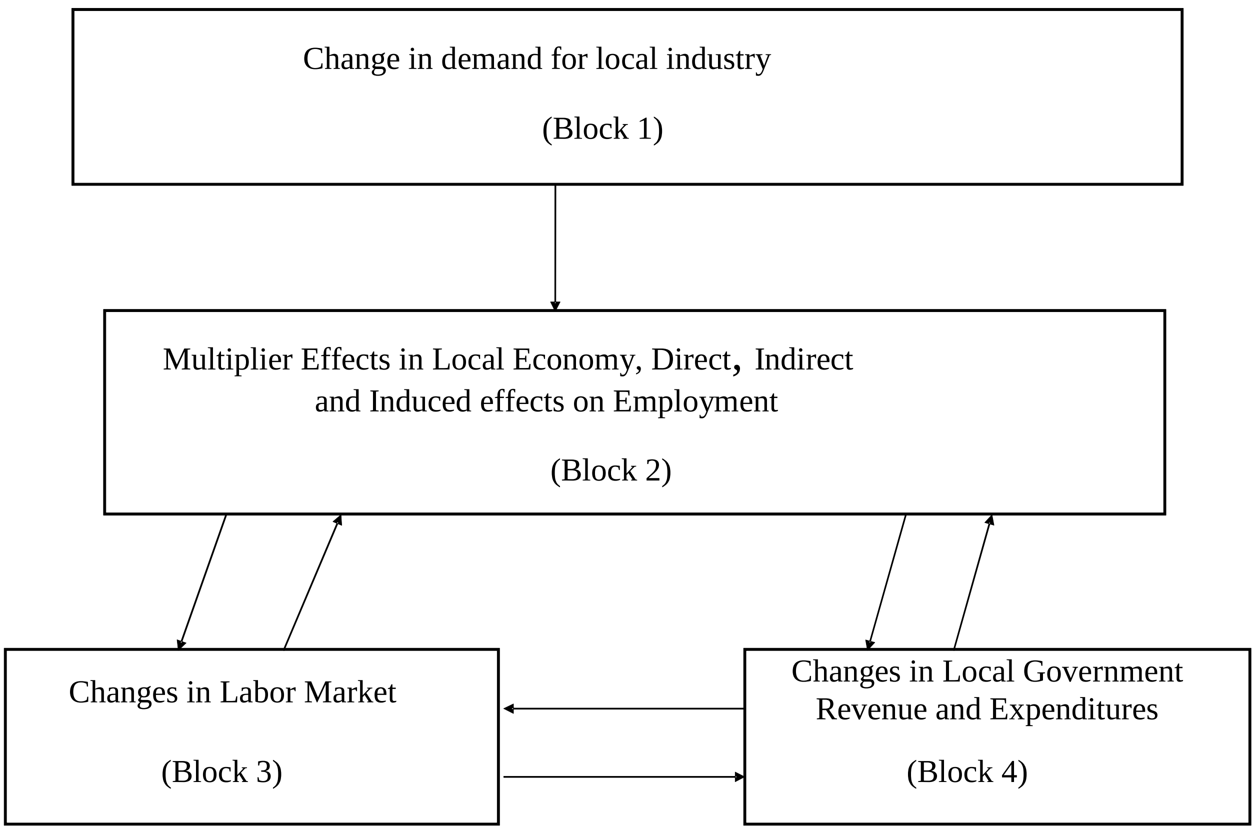

Figure 1. A Block recursive diagram highlighting the labor market in COMPAS modeling framework

Background of Labor Force Module in the COMPAS Framework:

COMPAS models use statistically estimated relationships to forecast changes in demographic, economic and fiscal conditions under exogenous changes in economic activity. The model includes a system of cross sectional econometrically estimated equations estimated for communities in respective states (Johnson, Otto and Deller, 2006). These estimates, though significant, might not perform well in terms of mean squared error differences, and the forecasting would not be accurate. In particular, labor markets involve a structural system where employment supply, employment demand and constantly changing between regions creating a constant change in flow of the labor force to meet demand both within and between regions.

Changes in labor markets and how it is influenced by the changes in employment demand are described hereafter. Estimation of the labor force module plays a key role in our model, as is also the case with other COMPAS- based models. The Louisiana labor force module estimates structural equations for labor force, in-commuters and out-commuters, which closely explains the relationship between employment demand and the supply of labor needed to meet that demand. In the COMPAS modeling framework, labor supply is a function of labor force, unemployment, out-commuters and in-commuters within a region. Similarly, labor demand is the function of the wage rate.. As can be seen in Figure 1, the labor force module lies between exogenous changes in employment and the ultimate fiscal effects (local government revenue and expenditures that occur in the local economy) in COMPAS (Block 3).

Local and regional labor markets play a vital role in COMPAS-based models. These models assume that economic growth is caused mostly by an exogenous increase in employment. Conceptually, the labor force module intersects labor force demand and labor force supply or X_D

$= X_S$,where X_D is labor force demand and X_S is labor force supply (Johnson 2006). The demand curve for the labor force is a function of the wage rate, or $X_D = f(w)$;

where w is the wage rate. We can invert the labor demand equation to obtain $w = g(X_D)$. We can also evaluate the supply as disaggregated into the following components

$$X_S = X_{LF} - X_U - X_O + X_I$$

where X_{LF} is the total labor force, X_U is the total unemployment, X_O is the total number of out-commuters, and X_I is the total number of in-commuters. We can then evaluate each component of the total labor supply as a function of employment as well as a vector of supply shifters (Johnson, Otto and Deller, 2006).

$$X_{LF} = f_L (w, Z_{LF}) = f_L (g (X_D), Z_{LF})$$

$$X_O = f_L (w, Z_O) = f_L (g (X_D), Z_O)$$

$$X_I = f_L (w, Z_I) = f_L (g (X_D), Z_I)$$

where Z is a vector of supply shifters for labor force, out-commuters, and in-commuters.

Objectives of the Study:

The primary objective of this study is to evaluate the relative performance of three state least squares models against alternative models for forecasting purposes. All equations are regressed to several economic and demographic variables that are supposed to impact the growth (positive or negative) of the dependent variables. For the purpose of this paper, we focus on labor force module (but the impacts could be seen on both labor market and fiscal sector), but further extension of the paper includes elaboration on fiscal module and its implications to fiscal health of a region.

Literature Review:

A plethora of studies have been performed on constructing a labor force and fiscal module and estimating parameter estimates for different purposes using OLS (non spatial) and spatial estimators. The labor force module is a demand driven framework based on employment demand (Johnson, Otto and Deller, 2006; Fannin et al., 2008; Swenson, 1996). The underlying assumption is that economic growth is largely due to the exogenous increase in employment in a region.

A concept of modeling the labor market was developed by Johnson(2006) where he assumes that economic growth of a community is based on the labor market that allots jobs between the in-commuters, out-commuters, currently unemployed and new entrants to the local labor market. The study has laid out a foundation on describing how the fiscal impacts in a region take place based on the labor force impacts of a region and vice-versa. A labor market is conceptualized and presented in the figure below where the author has provided ample reasoning on why the labor market plays a vital role in COMPAS based models.

Figure 2. A Conceptual Labor market

Johnson, 2006

The linking of labor force module with input-output models such as IMPLAN (impact modeling for planning) is highlighted by Swenson and Otto (1998). They constructed an Iowa economic/fiscal impact model (IE/FIM) to generate detailed information about economic, demographic and fiscal variables to local decision makers. An inter-relationship of the labor force module and a fiscal module is presented in the sense that the changes in employment demand and the population are major factors affecting local tax bases, local revenues and expenditures. Labor force, out-commuters and in-commuters were the three dependent variables used in the model whereas population was assumed to be a function of labor force and other variables that affect labor force participation rate.

Based on the Iowa economic/fiscal impact model, Johnson and Scott (2006) proposed and analyzed another model to provide the information needs to policymakers at federal, state and local levels. The model, developed in Missouri, was named the Show Me community policy analysis model. Labor market equations were created based on the spatial labor market developed earlier by Johnson (2006) where in-commuters and out-commuters are the major source of labor supply in a region and employment by place of work equals labor demand. The model was analyzed by a simultaneous system of equations where a three stage least squares regression method was used to evaluate the model since it is an efficient estimator in checking for existence of correlation between individual equation's error terms (Pindyck and Rubinfield, 1991).

A similar study has been carried out recently by Fannin et al.(2008) to evaluate the deep water energy impacts on economic growth and public service provision in Lafourche Parish, Louisiana. Authors created a Louisiana community impact model (LCIM) in a block recursive fashion based on the COMPAS modeling framework to enumerate the linkages among local economic activity and the demand for local government services. A conjoined input-output and econometric model was used to analyze the economic impacts of the region. A labor market has been defined as a market that can provide population estimates as the local economy changes and that where the demand for labor by firms in a local economy between in-commuters, out-commuters, unemployed and new entrants are allocated. In my study, I propose modifications in variables and the estimation procedure by inclusion of quantile and spatial methods that accounts for spatial heterogeneity.

There have been several studies regarding the construction of the fiscal module in COMPAS models and the use of spatial and non-spatial estimators for different purposes. These estimators are used in different fields of study, where the heterogeneity issue needs to be accounted in a more sophisticated manner. A comprehensive fiscal impact model for Virginia counties was estimated by Swallow and Johnson (1987), where they explained the model to forecast the economic, demographic and fiscal impacts of regional economic shocks. The entire analysis was carried out by estimating the sets of local government revenue capacity and local government expenditure equations. An extension and a slight modification of this work was presented by Shields, 1998, where he estimated different sectors of local economy using two revenue capacity equations, six expenditure equations and two housing market equations.

Using a three stage least square (3sls) approach, Johnson and Scott (2006) constructed and estimated a labor force module and fiscal module for all counties of Missouri. Their fiscal module included two revenue base equations, three revenue equations and six expenditure equations. Swenson and Otto (1999) provided continuity from earlier research and estimated an economic/fiscal impact modeling system for Iowa counties, where they introduced the concept of housing market equations. The fiscal module was quite similar to the one used by Swallow and Johnson, 1987, where they included six revenue capacity equations and various sets of expenditure equations. An extension of earlier studies was proposed by Evans and Stallmann (2006), where they proposed the Small Area Fiscal Estimation Simulator for Texas counties using a two-stage least squares procedure. A labor force module and fiscal module were estimated using a 14-equation model.

As stated earlier, spatial and non-spatial models are used across many disciplines. Franzese and Hays (2007) have used the spatial econometric models of cross-sectional interdependence in political science panel and time-series-cross-section data, where they demonstrated the econometric consequences of different specification and estimation choices in the analysis of spatially interdependent data and highlighted how to calculate and present spatial effect estimates. They considered four common estimators- non spatial OLS, spatial OLS, spatial 2SLS and spatial ML. They analytically examined the respective omitted variable and simultaneity biases of non spatial OLS and spatial OLS and then evaluated performances of all four estimators in bias, efficiency and standard error accuracy terms under more realistic conditions using Monte Carlo experiments. Their results showed that spatial OLS, despite its simultaneity, performs acceptably well under low to moderate interdependence strength and reasonable sample dimensions. They also concluded that spatial 3SLS or spatial ML may be advised for other conditions, but, unless interdependence is truly absent or miniscule, any of the spatial estimators unambiguously dominates on all three criteria the non spatial OLS commonly used in various empirical works in political science.

Our concentration in this paper is to evaluate the methods and techniques used by various scholars for forecasting performance and then applying to compare and contrast between the performances of estimators using several approaches. As suggested by many researchers, we will be estimating the performance by several quantitative methods where we analyze different indicators like mean error, mean square error, root mean square error and Theil's coefficients as a benchmark for comparison. This will be an innovative study in terms of comparing various types of estimators of a labor force module in COMPAS type models.

Data and Methodology:

Estimation is based on the COMPAS model for all parishes of Louisiana that includes all 64 parishes, where the variables for the labor force module were selected on the basis of Fannin et al (2008) and were modified depending upon the requirements of our model. Louisiana is a good candidate for such a test because of the heterogeneity of the local labor force within the state. The population, in-commuter earnings and out-commuter earnings equations are estimated by a cross-section Ordinary Least Square (OLS) model as a base control with three stage least squares and panel data model also estimated. Heterogeneity is defined based on diversity in size, population and influence of natural disaster in each parish. We estimate the model using the data mostly from the Bureau of Economic Analysis (BEA) regional economic data series (www.bea.org). The entire regression analysis is analyzed using STATA. The forecasting performance is evaluated based on the procedures outlined in Johnson, Otto and Deller (2006), and Kovalyova and Johnson (2006).

Empirical Specification of Labor Force Module:

The labor market equations in this module are based on the conceptual labor market discussed earlier in the paper. The three stage least square method is used in order to correct for the correlation, if any, present between the individual equation's error terms. Hence, three stage least squares is considered efficient since it incorporates cross-equation correlation into parameter estimates. Following the work by Johnson (1996); Swenson (1996); and Fannin et al. (2008), the Louisiana labor force module empirically specifies three structural equations for these variables.

The three basic labor force equations could be expressed as:

$$LABFOR = \beta_{10}+\beta_{11}EMP+ \beta_{12}UNEMP+ \beta_{11}OUTCOMM$$

$$INCOMM= \beta_{20}+\beta_{21}EMP+ \beta_{22}CONEMP+ \beta_{23}CONLABFOR+ \beta_{24}UNEMP$$

$$OUTCOMM= \beta_{30}+\beta_{31}EMP+ \beta_{32}CONEMP+ \beta_{33}CONLABFOR+ \beta_{34}UNEMP$$

Where, LABFOR (labor force), EMP (place of work employment), UNEMP (unemployment), OUTCOMM (out-commuters), INCOMM (in-commuters), CONEMP (contiguous employment) and CONLABFOR (contiguous labor force) are endogenous variables.

The labor market equation provides the information on all the components of labor supply and labor demand. Most employed (including self employed) workers commute some distance. The data that we use are organized as if jobs and workers were located in discontinuous locations. When data are recorded, some workers are identified as residents of a different location than that of their jobs. These workers are defined as commuters. This definition, however, is very much dependent on the arbitrary boundary of data cells; especially the size of the data cells. In practice, these data cells are always counties or census places.

As stated earlier, the primary purpose of this chapter is the performance measurement of different estimators and to check whether the uniqueness of cross-sectional units matter. This is performed by evaluating different estimators of a general labor force that takes into account heterogeneity. We are interested in choosing an optimal model that maximizes the forecasting performance for the labor force module equations in COMPAS models. A cross-sectional OLS, 3sls, and a panel approach will be applied in order to model the labor force.

We start with OLS/GLS framework where we take a single year's worth of data as performed by Johnson et al. (2006). The base year for estimation is 2008, which is a perfect match because of the fact that most parishes were measurably recovered from the serious damages caused by hurricanes Katrina and Rita. Next, we take into account three stage least squares model for the same year as OLS and then we take a multiple years worth of data to analyze the panel model. Sometimes a policy based on OLS might not yield the desired result as a certain subsection of the population does not react as strongly to this policy or even worse, responds in a negative way, which may not be indicated by OLS (Besley, Kuh and Welsch, 1980).

Comparing the performance of different estimators is an important step in the model building process since it can suggest the best model to be selected and different ways in which the model can be improved. Because of the availability of actual data for 2008, it is a simple matter to determine the accuracy and degree of discrepancy between generated outcome and the actual data. The performance of estimators is compared on the basis of quantitative evaluation methods. These methods include analysis of mean simulation error (ME), mean percent error (MPE), mean absolute error (MAE), mean absolute percent error (MAPE), mean square error (MSE), root mean square error (RMSE), root mean square percent error (RMSPE), and Theil's coefficient U1 and U2 (Johnson, Otto and Deller, 2006; Pindyck and Rubinfield, 1991, 1998; Theil, 1970, 1975). These performance metrics will be provided for both in-sample years (2008) and selected year's out-of-sample.

Results and Discussion:

Results from table 1 (see in Appendix) demonstrate the descriptive statistics of variables used in the labor market equations of the labor force module of Louisiana. As could be seen, there is lot of variability in the data set. The range for the maximum and minimum values is quite a bit for all the variables indicating variability in the data set. In addition, the mean and the standard deviation of all the variables are displayed in table 1. Results from table 2 demonstrate parameter estimates comparison of the OLS estimators, 3sls estimators, and panel estimators for all the three structural equations of the labor force module of Louisiana. Most of the signs in the parameter estimates are as expected; however, there are some counter-intuitive estimates. In case of in-commuters equation (for all models), it is obvious that an increase in the place of work employment of a region would attract more in-commuters. Similarly, a negative sign for the contiguous employment is consistent with theory, as it depicts that an increase in employment in the contiguous areas/regions would decrease the in-commuters since they would start working in their place of residence rather than commuting to other regions. Also, an increase of labor force in contiguous areas would increase the number of in-commuters in any region. The increase in unemployment would certainly lead to decrease in the number of in-commuters in the region.

In case of out-commuters equation, the negative sign of the contiguous variable indicates that an increase in the labor force in the contiguous regions would decrease the number of out-commuters from a region. However, an increase in number of employment in contiguous regions would increase a number of out-commuters to those regions. The negative sign of employment is not consistent with the theory, since an increase in place of work employment should attract more people from contiguous regions and the people within the region showing decrement in the number of out-commuters. This might be because of the fact that place of work employment is not attractive in terms of people's interest and salary as well. This is particularly the case when rural counties are contiguous to an urban or metropolitan county that attracts people for better paid jobs.

There is a mixed result of performance superiority as compared between OLS and 3sls regression models but both of these models have outperformed the panel model (Table 3). In the labor force equation, OLS is found to be outperforming 3sls and panel models in terms of mean error, root mean square percent error and Theil's coefficient. For the in-commuters and out-commuters equations, mean error, root mean square percent error and Theil's coefficient seem to be lower in 3sls model as compared to OLS and panel data models. This indicates the supremacy of 3sls model compared to other models because of the fact that these are the errors in calculation and lesser are the errors, better is the model. Theil's coefficient is calculated based on root mean square error and zero value of the coefficient indicates perfect prediction and any value up to 10% is considered effective.

Average error measures are not the perfect method for evaluating the performance of entire region. We can, therefore, take individual parish data and evaluate the performance of estimators in terms of quantitative measures like mean error, mean percent error and root mean square error to figure out how much the predicted value deviates from the actual value. For the labor force equation (in case of OLS), we could see that the average mean error, mean percent error and root mean square percent error are 462.29, 0.021 and 0.069 respectively (Table 3). However, because of the heterogeneity in space, some parishes like West Feliciana, Plaquemines, Cameron, East Baton Rouge, Iberville, and Orleans are not performing as good on average, since their predicted values are measurably off their actual values and thus are the reason for higher error values. On the contrary, parishes like Bienville, Concordia, Natchitoches, Richland, St. John the Baptist, and Madison are performing better than the average error measures as the difference between the predicted and actual values are close to zero.

Conclusion and Limitations:

Much of the original COMPAS models were developed in Midwestern states where there was measurable homogeneity in economic and fiscal structure of rural regions (the focus of many of these models). Our results identify whether three stage least squares models have increased performance versus OLS and panel regression methods in labor force module COMPAS approaches. These results will be helpful to those community modelers desiring to estimate cross-section labor force modules for forecasting in states that have much greater heterogeneity among local government units.

This study showed that the newer alternative methods are now available to address the limitations of OLS and panel models. Three stage least square regressions have advantages over COMPAS model and OLS regression in improving the model performances. Three stage least squares regressions are hence proposed as another COMPAS estimator alternative since they could be used in order to correct for the correlation, if any, present between the individual equation's error terms. Besides three stage least square regression, other estimators can also be used to measure the performances of the model. Spatial estimators could also be used as other alternatives to the COMPAS model. This would be a future extension to this paper.

An evaluation of the alternative methodologies performed in this study are expected to give regional economic modelers better information from which to choose when seeking to construct models projecting different modules. Using the data from different sources, this study develops a model to forecast different sectors of labor force module using simple linear, panel and three stage least square regression. Increased performance of these estimators will narrow the confidence interval around these forecasts and increase the demand and application of these models by local governments.

One of the limitations of the COMPAS model is that it is mostly used to evaluate the impacts within a small city, region or a county, yet our study focuses on almost all the parishes of Louisiana. This forces us to evaluate the performances on a basis of state average, which in fact, is not the ideal way to forecast the performance, because of the heterogeneity in regions within the state. If we evaluate on the basis of each parish, we could be able to identify the error measures; that is, how much of a predicted value is deviated from the actual value. Also, data used in COMPAS models are mostly cross sectional and hence the heterogeneous nature of the region in a state gives rise to the issue of heterogeneity.

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APPENDIX

Table 1: Variable description and summary statistics, Louisiana

Variable Name	Mean	Standard Deviation	Min	Max
Labor Force	29,766	38,341.16	2,396	236,340
In-commuters	10,754	19,889.65	272	118,882
Out-commuters	10,552	13,194.24	488	86,044
Employment	28,325	41,996.63	1,944	221,739
Unemployment	1,536	2,130.65	146	13,931
Contiguous Employment	134,011	87,361.88	16,055	452,214
Contiguous Labor Force	136,396	85,903.89	21,046	432,621

Table 2: Parameter estimates for OLS, 3sls and panel regressions of Louisiana labor force module

Labor Force Module	Linear (OLS)		3SLS		Panel	
	Coeff.	t-stat	Coeff.	z-stat	Coeff.	z-stat
Labor Force (Dep var) (log-log model)						
Employment	0.464***	4.25	0.730***	4.43	1.039***	26.55
Unemployment	0.192	1.51	0.193	1.59	-0.064	-1.12
Out-commuters	0.337***	5.56	0.030	0.21	0.077	1.00
Constant	1.026***	6.66	1.198***	3.91	-0.484	-0.71
In-commuters (Dep var) (log-log model)						
Employment	1.071***	4.72	1.075***	4.68	0.309***	10.76
Contiguous Employment	-0.097	-0.23	-0.214	-0.67	-0.013	-1.38
Contiguous Labor Force	0.084	0.19	0.048	0.14	0.016***	3.22
Unemployment	-0.029	-0.11	-0.031	-0.12	-0.421***	-11.56
Constant	-3.732***	-4.99	-3.590***	-4.40	8.246***	60.31
Out-commuters (Dep var) (log-log model)						
Employment	0.557***	3.27	0.555***	4.52	0.277***	9.16
Contiguous Employment	0.492**	2.57	0.450*	1.91	0.009	0.88
Contiguous Labor Force	-0.287	-1.30	-0.240	-0.93	-0.016***	-3.89
Unemployment	0.312	1.60	0.313**	2.28	-0.365***	-9.41
Constant	-0.995**	-2.14	-1.045**	-2.18	8.643***	78.89

*****/**/*** indicate statistical significance at 1%, 5%, and 10% levels respectively

Table 3: Average performance estimation measures for dependent variables in labor force module, Louisiana

Expenditure Category	Linear (OLS)	3sls	Panel
Labor Force			
yhat-y	462.29	538.441	4283.192
(yhat-y)/y	0.021	0.023	0.018
$\{(\text{yhat-y})/\text{y}\}^2$	0.069	0.072	0.232
Theil's Coeff (U1)	0.010	0.012	0.054
In-commuters			
yhat-y	-1737.74	-1675.8	-7097.43
(yhat-y)/y	0.087	0.081	0.331
$\{(\text{yhat-y})/\text{y}\}^2$	0.227	0.224	1.549
Theil's Coeff (U1)	0.022	0.021	0.254
Out-commuters			
yhat-y	129.063	-58.83	-491.9
(yhat-y)/y	0.026	0.013	0.159
$\{(\text{yhat-y})/\text{y}\}^2$	0.064	0.062	0.911
Theil's Coeff (U1)	0.011	0.010	0.189