# Determinants of Per-Capita Personal Income in Oklahoma City

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## Introduction

Per-capita Personal income in Oklahoma City[1] has steadily increased over the past thirty years. Although there has been a significant increase in Oklahoma City per-capita personal income (pcpi), it has consistently been lower than the national average. In the past thirty years, Oklahoma City pcpi has been above the national average only once for a brief period between 1977 and 1985. Moreover, since 1985, Oklahoma City pcpi has not only been below the United States average, but it has grown at a slower rate than that of the U.S.

In addition to remaining below the average nationally, pcpi in Oklahoma City has also remained below that of its neighboring cities. In the past thirty years, Oklahoma City has not once had higher pcpi than Tulsa, Wichita, or Dallas. Furthermore theses other major cities have consistently been above the U.S. average. Despite these cities similar resources and histories, Oklahoma City has had slower growth and a weaker economy. This paper will examine the causes of variation in Oklahoma City income, as well as briefly look at some of the possible reasons for the difference between pcpi in Oklahoma City and other cities in the region.

## Factors affecting PCPI

Many variables were examined to determine their effect on pcpi. The original intent of this research was to determine the effects of consumption, investment, and government spending, on pcpi. This task was not easily accomplished. Finding data on these series turned out to be difficult because it either did not exist, or could not be found for enough years to make it valuable. Despite this challenge, I did however discover several variables consistently recorded over the past thirty years which provide insight into determining income.

[1] For the purpose of this paper we will use Oklahoma City to refer to the Oklahoma City Metropolitan Statistical Area as defined by the Bureau of Economic Analysis. This includes Oklahoma, Cleveland, McClain, Pottawatomie, Logan, and Canadian Counties.

Population is one of the variables I examined. One would expect a larger population to allow for higher pcpi. Many large companies (especially retailers) have population minimums that must be met before they will locate in a city. Also, larger cities tend to have more high skill, high paying jobs. I expected to see pcpi increase as population increased.

The effects of the supply and demand of oil were also examined in my research. Oil is a large industry in Oklahoma as a state, as well as in Oklahoma City, so changes in the supply and demand of oil should have distinguishable effects on income. I looked at several options for measuring the effects of changes in the oil market. The average price of oil[2] is the most obvious indicator of changes in the oil market, and is easily tracked. Another way to gauge the effects of changes in the oil market on Oklahoma City is to look at the portion of total income in Oklahoma City derived from oil extraction. This gives a better idea of how the Oklahoma City oil industry is changing. The effects of changes in the oil market in an oil-producing region such as Oklahoma City are interesting. An increase in the price of oil will have two counteracting effects on income. First, income will increase because money will begin flowing into the region as production and profit margins increases. There will also be the counter effect of increased cost of production in all other industries. This is the effect seen in non oil-producing regions. Therefor the net effect could be positive or negative.

Employment is another variable examined in this paper. There are a number of ways to measure employment. First, it can be measured as the total number of jobs. The major problem with using this method is that the total number of jobs is highly correlated with population, and it is therefore difficult to use both of the variables in regression analysis. It can also be measured by looking at the unemployment rate. A third way of viewing the effects of changes in employment on pcpi is to look at the percent of the total population employed (total employment/population).[3] This variable attempts to account for changes in the size of the available labor force (worker/dependent ratio) as well as

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[2] Measured in dollars per barrel.

[3] This is in essence a modification of the standard worker/dependent ratio, where

Worker/dependent ratio = Number of people between 16 and 65 / total population

= the portion of the population available to work.

changes in the unemployment rate. This also causes problems as it does not allow you to distinguish between changes in the size of the labor force and changes in the size of the working age population.

We expect to see pcpi increase as a higher percent of the population is employed, even if average wage does not change.[4] Changes in total employment could have a positive or a negative effect on pcpi. There could be a negative effect if the population increased at a faster rate than total employment, or if additional jobs paid lower wages.

Another variable that could possibly affect pcpi is the tax burden. Here you can look at the effects of individual as well as corporate income tax, and sales tax. As individual income tax increases, we expect pcpi to decrease. This makes the state and city less attractive, especially when compared to states such as Texas which have no personal income tax. Increased sales tax should have the same effect, although it may be less significant because people are less likely to consider sales tax when choosing a place to live. Changes in corporate income tax should also be negatively correlated with pcpi. Companies are less likely to invest in a state where they will have to pay higher taxes. All of these variables can be measured in terms of percentage rates, or as the average amount paid per dollar of income.

Transfer payments were another variable I investigated. Because transfer payments are a component of total income, I examined them as percent of total income derived from transfer payments, rather than the income derived from transfer payments. In theory, transfer payments should have a net effect of zero. Showing that transfer payments do affect income would give some indication as to whether Oklahoma City has a net inflow or a net outflow of transfer payments.

The components of income and their relative changes were also examined. This was in an attempt to determine whether a change in the industry mix in Oklahoma City would effect pcpi. The portion of income derived from the service sector in Oklahoma City has steadily increased over the past thirty years, while the portion of income derived

[4] Although theoretically possible, it is extremely unlikely to have an increase in the percent of the population employed coupled with a decrease in pcpi. This would imply that total income decreased while the number of people working increased, assuming population stayed the same.

from manufacturing, although much more variable, has decreased. It seems feasible that this change in the makeup of income could significantly affect pcpi.

The last variable I examined was resident adjustment. Resident adjustment is the net inflow of the earnings of inter-city commuters. For Oklahoma City (as for most major cities) this has always been a negative number, indicating that more money is being earned by people commuting to Oklahoma City than by people commuting from Oklahoma City. As with transfer payments, this must be looked at as its portion of total income, because it is a component in figuring total income.

**Estimated Models**

Several models were developed for explaining Oklahoma City pcpi. Each has its own strengths and weaknesses. The model that most accurately explains Oklahoma City pcpi is:

(1) $$PCPI = -1807.41 - \underset{(0.001679)}{0.006262}(Population) + \underset{(0.00572)}{0.06224}(Employment) - \underset{(4.93 \times 10^{-9})}{4.15 \times 10^{-8}}(Employment^2) - \underset{(34.516)}{81.815}(Oil/Income\ ratio)$$

where population is the total number of people in Oklahoma City and Employment is the total number of jobs in Oklahoma City. There is no weighting in this measure so a part time job counts just the same as a full time job. The oil/income ratio is the portion of total income derived from oil and gas extraction.

(2) $$Oil/Income\ ratio = income\ derived\ from\ oil\ and\ gas\ extraction\ /\ total\ income.$$

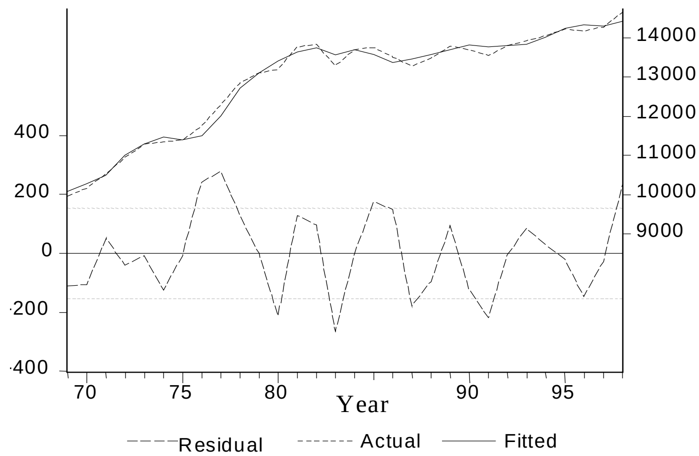
The standard errors of each coefficient are given in parenthesis under the coefficient.[5][6]

As you can see in Figure 1 this model provides a good fit for the in sample data. The $R^2$ for this model is over 98%, indicating a high level of explanatory power. The major complication with this model is that it suffers from a severe case of multicollinearity. For obvious reasons, total employment and population will be highly

[5] See attachment 1 for full results on this equation.
[6] All values monetary values have been converted to real terms. See Attachment 11 for data sources.

correlated. This problem is persistent throughout this research, and is unavoidable with this type of data. Multicollinearity will cause the variance of our coefficients to be inflated. It can also cause coefficients to change sign and magnitude due to slight changes in specification or data sets. Because the variables affecting income are all so highly correlated with each other, determining their individual effects on income is difficult.

Figure 1: Equation 1 predicted values verses actual




**Population**

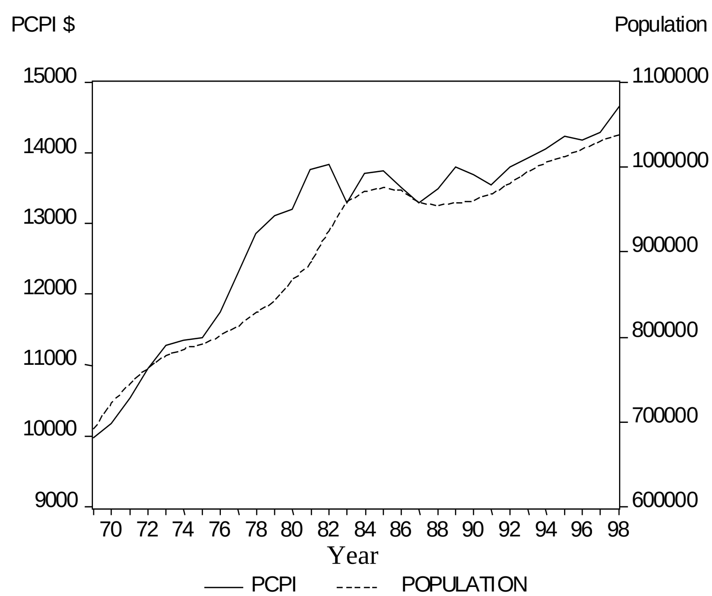
Population is an interesting variable in this model because it is a part of the equation

(3) Pcpi = Income/Population.

Therefor if population increases without a change in total income, pcpi will decrease. Of course population will never actually increase with out an increase in total income, although it may increase at a faster rate than total income. If this is the case, the coefficient on population will be negative. I originally hypothesized that population would have a positive effect on pcpi, reasoning that a larger population would allow for higher productivity and would make the city more attractive to large corporations. In our estimated model, population has a coefficient of –0.006262, indicating that for each additional thousand people in Oklahoma City, pcpi is expected to decrease by just over six dollars. This may not appear to have a great impact, but population in Oklahoma City has grown by 350,000 in the past thirty years. According to our model the effects of this population growth (holding the other variables constant) has been a decrease in pcpi of approximately $2,200.

The negative coefficient does not support my original prediction, but upon closer examination such a relationship is logical. It indicates that population is growing faster than income. This is what we would expect if we had an influx of people, while capital did not grow (or did not grow as fast). In this case we would expect the average wage to fall.

Figure 2: Pcpi and Population Growth




One challenge with using population as a determinant of pcpi is that it is difficult to ascertain the causal relationship between population changes and changes in pcpi. Figure 2 illustrates the timing of changes in population and pcpi. From this graph, it appears that income may actually drive population, and indeed this is logical. People will migrate to profitable areas. The variable remains in the model because there must also be a reciprocating effect. That is, the two variables affect each other. Also the primary reason it appears that income leads population in figure 2 is the increase in pcpi in the mid 1970s. This increase was prior to the population increase. Another variable might account for this one time significant increase in pcpi. In that case it is not clear that population changes before income.  Having population incorporated into the model helps us avoid a specification bias.

**Employment**

The coefficient on our employment variable is 0.06224.  This positive coefficient makes sense because any additional job will always raise total income.  Holding population constant, equation (3) shows us that pcpi will always increase with an increase in employment.[7]  Figure 3 shows us that employment is obviously correlated with income.

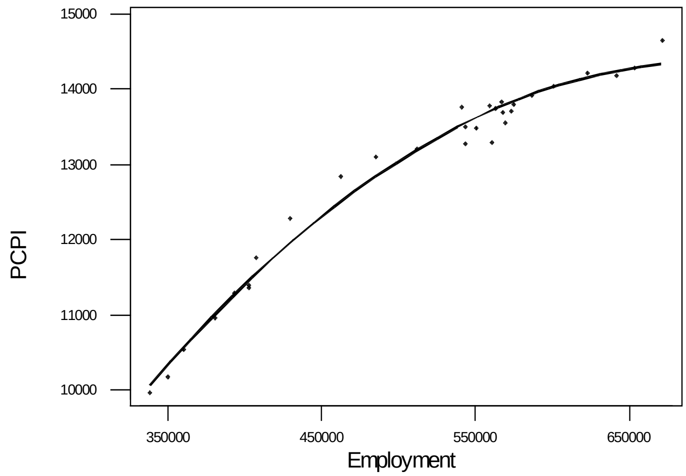
Our model also contains a quadratic term for employment. This is because as employment increases, pcpi tends to increase at a decreasing rate, as shown in figure 4 The negative coefficient accounts for this.  Because the relationship between population and pcpi is not linear, the coefficients are harder to interpret. The change is no longer the constant coefficient, but rather decreases as employment increases.

There is one major obstacle with using employment in the estimated model.  This is its high correlation with population.  It is sensible that population and employment would tend to move together.  Population would not continue to grow if employment stayed the same, and the converse is also true.  This high correlation makes it hard to discern which variable causes what change in pcpi, thus making our coefficients less valuable.   It also inflates the variance of the variables.

Figure 3:  Employment vs Pcpi


[7] This is assuming that the makeup of the job market does not change, i.e. the increase in employment does not coincide with an increase in the portion of lower paying jobs.

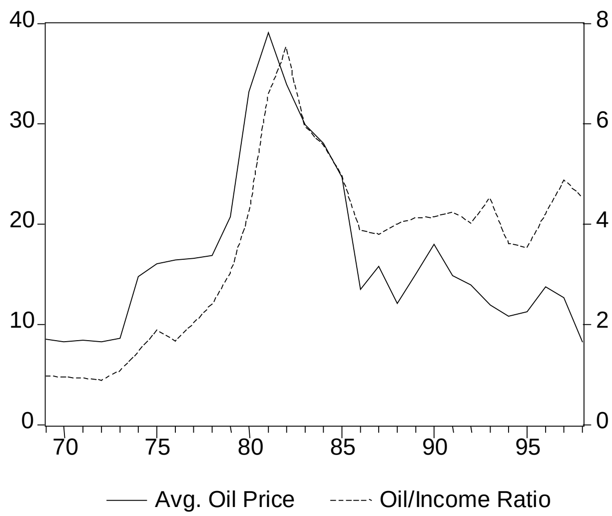
Figure 4: Pcpi Verses Employment




## Oil/Income Ratio

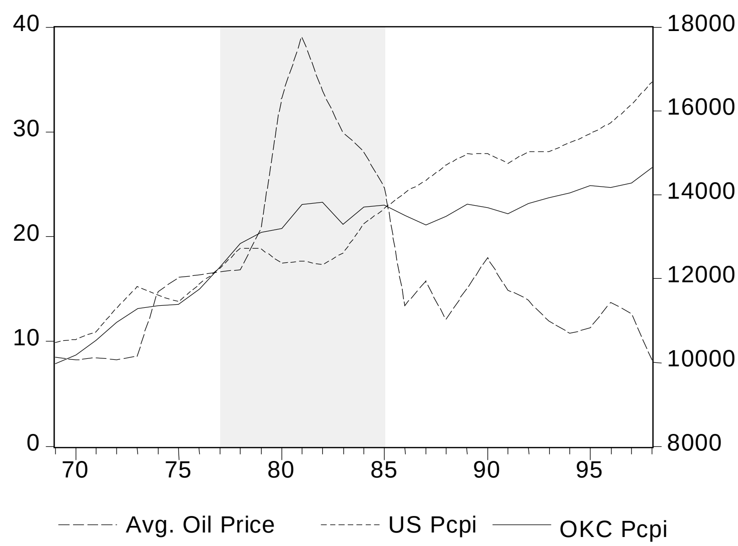
The oil/income ratio is the ratio of income derived from oil and gas extractions over total income. This gives an idea of how changes in the oil market affect Oklahoma City. We use the oil/income ratio in lieu of average oil price for several reasons. This measure gives us a better idea of what is happening in the local Oklahoma City area. The oil/income ratio tends to be a better indicator of how changes in the larger oil market affect Oklahoma City. For this reason, it is more highly correlated to changes in Oklahoma City pcpi. Changes in the oil/income ratio tend to be seen in the year after the corresponding change in the average price of oil. This can be seen in Figure 5.

Figure 5: Oil/income Ratio vs. Avg. Oil Price



The coefficient in the estimated model is –81.815. This tells us that as the percent of income derived from oil and gas extractions increases by one percent, pcpi is expected to drop by approximately $82. Between 1977 and 1985 are the only years when Oklahoma City pcpi exceeded the national average. By graphing Oklahoma City pcpi against the national average, and then superimposing average oil price on top of this graph, it is easy to see the relevance of the oil market on pcpi. This is illustrated in figure 6.[8] The shaded period in the graph corresponds to the time period in which Oklahoma City pcpi exceeded the national average. This time period also corresponds to a dramatic increase in the average price of oil, and therefor to the increase in the Oklahoma City oil/income ratio. Although it appears that the increase in the price of oil might have had a slight positive effect on Oklahoma City pcpi, it had a much more noticeable negative effect on the United States pcpi as a whole. This is the primary reason Oklahoma City was above the national average during this time period. Statistically we actually show that the oil/income ratio is negatively related to Oklahoma City pcpi (as is the average price of oil). This tells us that the negative effect is not as severe as in the rest of the country.

Figure 6: Effects of oil price on Pcpi.




[8] For this graph we use average oil price instead of the oil/income ratio because the average oil price can be compared across regions. It doesn't make sense to look at the oil/income ratio in Oklahoma City compared to national pcpi.

Although the model which best predicts pcpi in Oklahoma City uses the oil/income ratio, it is often better to talk in terms of average price of oil, as we have been doing. This is because it more easily allows us to compare the effects of changes in the oil market across regions. Later in the paper we will compare Oklahoma City to its neighboring cities. Data on oil production for several of these cities is not disclosed.[9] In order to accurately compare the between Oklahoma City and these cities, another model using average oil price rather than the oil/income ratio was developed. Although this model is slightly less accurate for looking at Oklahoma City data, it has the benefit of being easily compared across regions.

$$\text{(4)} \qquad \text{Pcpi} = -1702.86 - \underset{(0.00204)}{0.00727}(\text{Population}) + \underset{(0.00721)}{0.06514}(\text{Employment})$$

$$-\underset{(5.16 \times 10^{-9})}{4.43 \times 10^{-8}}(\text{employment}^2) - \underset{(5.91)}{12.337}(\text{Avg. Oil Price})$$

where the standard errors are given in parenthesis under their coefficients.[10] This model will be used later when comparing pcpi in Oklahoma City to that of its neighboring cities. It is introduced now to give a better idea of the effects of the oil market on Oklahoma City pcpi. The average price of oil is not as significant as the oil/ income ratio in determining pcpi, but at a five percent significance level we still reject $H_0$ that it is not a significant variable.[11] The Durban-Watson statistic on this equation, although still in the inconclusive range, is lower than on the original model, indicating it is more likely to suffer from serial correlation in the error terms.

The reason for introducing this model now is to show that our original model specification is fairly accurate, as far as the effects of the oil market are concerned. The oil/income ratio is correlated with population and employment, causing inflated variances and making the coefficient questionable. The average price of oil is not correlated with population or employment, so looking at this model gives us an idea of how accurate our original model is. Notice that the coefficients on population and the two employment terms are virtually the same between the two models. Furthermore, average oil price and

[9] The data is not disclosed because there are either to few companies or because one company has to large a market share.

[10] For full results on this model, see attachment 2

the oil/income ration have the same sign. Because average oil price is not correlated with the other variables, we can safely say that the true effect of increasing oil prices is a decrease in pcpi.

**Insignificant Variables**

Many variables were examined to determine their effects on pcpi n Oklahoma City. For several of these variables, we could not reject the $H_0$ that their true coefficient was equal to zero, suggesting their insignificance. Tax burden fell into this category. Dummy variables were set up to track the changes in individual income tax, corporate income tax, and sales tax.[12] In all of these cases, changes in the tax structure could not be significantly tied to change in pcpi. For individual income tax, the dummy variables corresponded to the highest marginal tax rate. This is an imperfect measure, because the marginal rate structure can change while the highest bracket stays the same. For this reason individual income tax was also measured as the average income tax paid per $1,000 of personal income. This variable also has a flaw. As pcpi increases, people will move into higher tax brackets, causing the average income tax per $1,000 to increase. This variable appeared to be significant in some specifications of the model (as insignificant variables were being dropped, while other insignificant variables still remained in the model), but did not appear significant in our final specification.

In all of the model specifications where income tax per $1,000 of personal income was significant, it had a positive coefficient. This seems counterintuitive, but is probably due to the movement of people to higher income tax brackets. This indicates that an increase in pcpi is causing the increase in income tax per $1,000, and not the other way around. For this reason income tax per $1,000 income would not a determinant of pcpi, even if it had been a significant variable in our model.

The portion of income derived from transfer payments, and the ratio of net resident adjustment to total income also can not be shown to be significant in the determination of pcpi. These two variables were eliminated from the model early on and

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[11] Average oil price has a p-value of 0.047, where as oil/income ratio has a p-value 0.026.

have little correlation with pcpi. Changes in the composition of industries in Oklahoma City also appeared to be insignificant.

**Regional Comparison**

As well as lagging the national average pcpi, Oklahoma City also has a lower pcpi than its neighboring cities. The pcpi in Dallas, Tulsa, and Wichita has consistently remained above that of Oklahoma City, as well as the national average. Attachment 3 graphically illustrates how Oklahoma City pcpi compares to these three cities' as well as the U.S. average. Moreover, out of the three hundred thirty five MSAs in the United States, Oklahoma City ranked two hundred sixteenth in 1998 in terms of pcpi. Now we will briefly examine some of the possible reasons why these cities with histories and resources similar to those of Oklahoma City have economically out performed it.

Besides lying below the national average, the past fifteen years have seen Oklahoma City pcpi growing at a slower rate than the national average. Since 1985, when Oklahoma City pcpi once again fell below the national average, their have only been three years in which it has grown at a greater rate than U.S. pcpi. Over this time period Tulsa and Wichita have done a better job of keeping up with the U.S. pcpi growth rate, and Dallas has exceeded it.

It is also interesting to note from attachment 4 that pcpi in Oklahoma City has exhibited a less volatile pattern than the other cities in the region. Although Oklahoma City pcpi has remained below that of Dallas, Tulsa, and Wichita, it has been more constant, experiencing less severe fluctuations. Attachment 5 gives the mean and standard deviations of the growth rates for each city. These values also lead us to believe that Oklahoma City pcpi is subject to less fluctuation than its neighboring cities. The formal test given in attachment 6 confirms that at a five per-cent significance level, Oklahoma City's growth rate is less variable than that of its neighboring cities.

In this section we will examine how well the model developed for Oklahoma City can be extended to the other cities in the region. We will develop models for these cities,

[12] All of these variables were measured at the state level. Data about local tax burdens was not readily available, and is inconsistent throughout the Oklahoma City Metropolitan Statistical Area (MSA). Sales tax varies from county to county, and town to town inside the Oklahoma City MSA.

using the same variables as we did the Oklahoma City model, and compare the coefficients. We will use the model containing the average price of oil rather than the oil/income ratio (equation 4). This allows our model to be more versatile, and avoids the problems caused by non-disclosed data in some cities. This will give us an idea how well our model can be applied across regions.

**United States**

It might be expected that our model would do a poor job of estimating U.S. pcpi. Even in the unlikely case the U.S. had the same specification, because population and employment are measured in raw terms, their coefficients would be much different. Indeed this is the case. Regressing U.S. pcpi on the variables specified in the equation for Oklahoma City pcpi gives the following regression.[13]

(5) $$\text{US Pcpi} = -3516.39 + \underset{(0.000027)}{0.000204}(\text{Emp.}) - \underset{(1.1 \times 10^{-13})}{4.922 \times 10^{-13}}(\text{Emp.}^2) - \underset{(5.17)}{28.58}(\text{Avg. oil price})$$

Notice that population is not a significant variable in this equation. Population may be a significant variable for individual regions, but not for the nation as a whole because it is easier for people to move around inside the U.S. than to move in and out of the country. The Durban-Watson statistic on this equation is also low (0.84), indicating there are other significant variables in determining U.S. PCPI that may not be significant in determining Oklahoma City pcpi.

Because total employment in the U.S. is much larger than total employment in Oklahoma City, the coefficients on the two employment terms in this model are much smaller than the coefficients on the Oklahoma City model. This makes comparison of the employment variable difficult. The most interesting aspect of the equation developed for U.S. pcpi is the coefficient on the average price of oil. This indicates that an increase of one dollar per barrel of oil is expected to lead to a decrease in pcpi of just over twenty-

[13] For full results see attachment 7

eight dollars. This is over double the expected decrease in Oklahoma City pcpi due to the same change in the price of oil

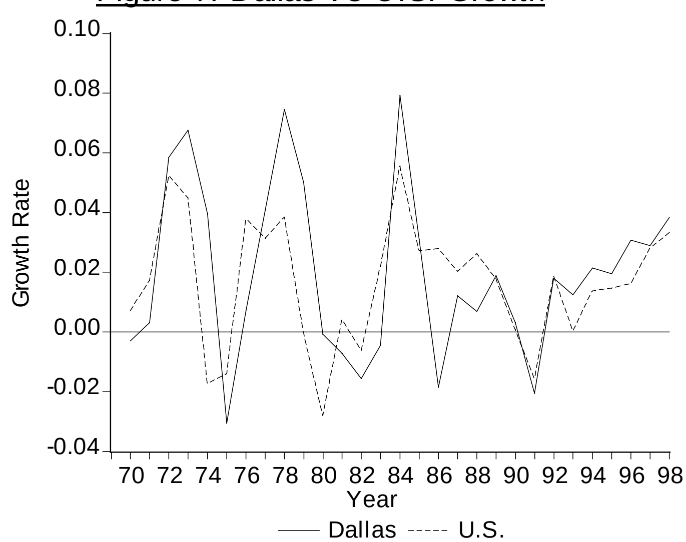
**Dallas**

As can be seen on attachment 3, changes in Dallas pcpi follow changes in U.S. pcpi more closely than the other cities in the region. This close relationship between the patterns of growth in Dallas and the U.S. can be seen in figure 7. Dallas does not appear to follow the same trend as Oklahoma City. This can be verified by our estimated equation for Dallas.[14]

(6) $$\text{Pcpi} = 7843.238 + 0.005267(\text{Employment}) + 33.908(\text{Avg. Oil Price})$$
$$\qquad\qquad (0.182) \qquad\qquad\qquad (9.733)$$

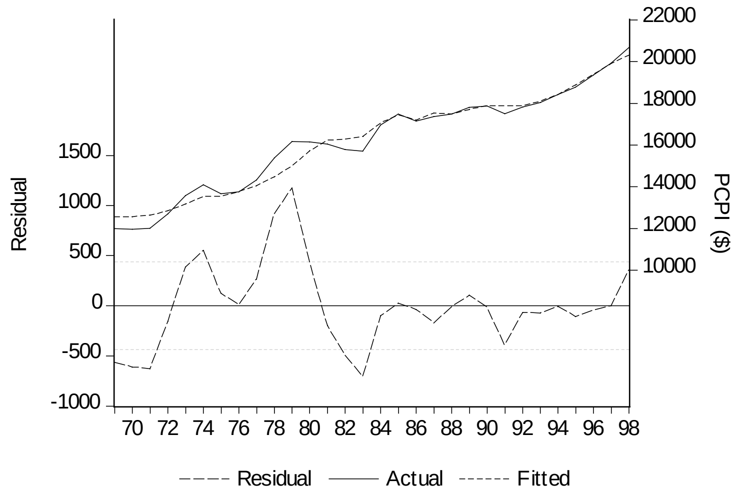
The model developed for Oklahoma City does a particularly bad job of estimating Dallas pcpi. The only variables significant in both models are employment and average oil price. The Durban-Watson statistic is 0.62, indicating a severe case of autocorrelation between error terms. There are obviously some variables that significantly affect Dallas pcpi which have been left out of our Oklahoma City model. In figure 8 the effects of the serially correlated error terms are visible.

Figure 7: Dallas vs U.S. Growth




[14] For full results see attachment 8

Figure 8: Dallas Actual vs Fitted




Although the Dallas model has an $R^2$ of 0.97, it is obvious that the model has some fundamental flaws. Employment and the price of oil may account for a large portion of changes in income, but do not account for a significant amount of the variability. This indicates tat there are some differences in the drivers of pcpi in Oklahoma City and Dallas. These may also be the variables that account for the substantially (and consistently) higher pcpi in Dallas as compared to other cities in the region.

**Wichita**

Pcpi in Wichita more closely follows a pattern resembling that of Oklahoma City's pcpi. The estimated model for Wichita is:[15]

(7) Pcpi = 18,206 – 0.05822(Population) + 0.0844(Employment)

*(0.4679)* *(0.004245)*

Once again, only two variables prove to be significant. Although there are probably still some significant variables missing from this model, it dose a better job of fitting the data than do the models developed for Dallas and the U.S. The Durban-Watson statistic of 1.23 falls in the inconclusive region when testing for serial correlation in the error terms. An interesting note about this model is that the constant term is above the all of the

[15] See attachment 9 for full results.

observed values of pcpi in Wichita. Because of this, the population coefficient must have a larger (negative) impact on the model than in the other estimated models. The employment coefficient is very similar to the coefficient on the Oklahoma City model, but is missing the quadratic term. The very large coefficient on the population term is probably due in part to multicolliniarity, caused by the high correlation between the two variables in the model. The coefficient on employment is close to the estimated coefficient on population for Oklahoma City.

The severe multicolliniarity in this model makes the model implausible. Because the coefficient on population has a greater negative effect than the positive coefficient on employment, and because population will always grow faster than employment, this model suggests that pcpi could never get above $18,206.30. Although this model does a good job of estimating pcpi in the sample used, it is likely to fall apart when applied to a broader range of observations.

**Tulsa**

The model estimated for pcpi in Oklahoma City does remarkably well when used for Tulsa. The estimated model for Tulsa is:[16]

(8) $$3{,}518.651 - \underset{(0.00247)}{0.037304}\,(\text{Population}) + \underset{(0.00788)}{0.13886}(\text{Employment})$$

$$-\underset{(8.71 \times 10^{-9})}{1.96 \times 10^{-7}}(\text{Employment}^2) - \underset{(5.589)}{12.4802}(\text{Avg. Oil Price})$$

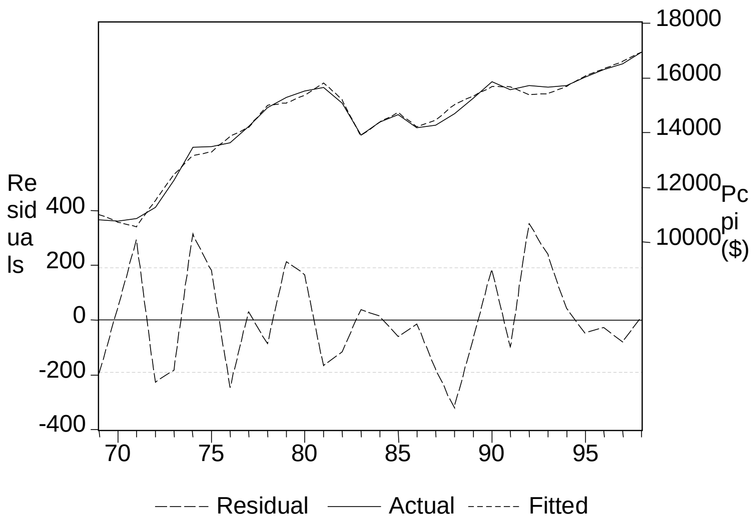
All of the significant variables for Oklahoma City pcpi are also significant in the Tulsa model. The Durban-Watson statistic is 1.87. This tells us that at a five percent significance level, we can reject the null Hypothesis that there is autocorrelation in the error terms. This is illustrated in figure 9. This specification actually seems to fit the Tulsa data better than it does the Oklahoma City data. I have not tested to see whether there are other variables that appear to be significant in determining pcpi in Tulsa, but the model given seems to account for most of the variation in is pcpi, explaining 98.9% of its variability.

[16] See attachment 10 for full results.

The coefficients on the Tulsa model are also remarkably similar to those on the Oklahoma City model. The larger (negative) coefficient on population and the larger (positive) coefficient on employment account for the larger variance in the rate of growth in Tulsa. An increase in employment is expected cause a larger increase in pcpi in Tulsa than it would in Oklahoma City. The accompanying increase in population is expected to only partially offset this increase,[17] therefor employment and population changes have a greater effect on Tulsa pcpi than they do on Oklahoma City pcpi. Notice that the coefficients on average oil price for the Tulsa model and the Oklahoma City model are virtually identical. Because these are just estimates of the true parameters, it is not unreasonable to assume that the actual parameters are the same for the two models.

The Tulsa model suffers from the same problems with multicolliniarity as the Oklahoma City model. Because of this we must remember that, although the estimated parameters look good and make sense, there is the chance that the true parameters may actually be much different than the ones we have estimated. The average price of oil is the exception to this. It is not significantly correlated to any of the other variable in the model, and we can therefor be fairly confident in its estimation. This may be why it has virtually identical parameters in the Oklahoma City and Tulsa models.

Figure 9: Tulsa Actual vs Fitted




[17] Employment$^2$ would also partially offset the increase in pcpi, but at all reasonable values of employment, it would not overtake the increase caused by the positive coefficient on employment.

**Conclusion**

This paper has examined two models for explaining the changes in Oklahoma City pcpi. Both of these models are based on the same principles, and differ only in their measurement of the effects of the oil market on pcpi. The models developed give insight into the determinants of pcpi. From the data available, population, employment, and changes in the oil market significantly affect pcpi.

Population seems to have a negative effect on pcpi in Oklahoma City. This is probably due to the fact that as labor increases without an equal increase in capital, wages will drop. Total employment has a positive effect on pcpi. Total employment and population typically move together. The increase in pcpi due to the increase in employment is expected to offset the decrease in pcpi due to increased population. Employment also has a significant quadratic term, indicating that as employment increases, is has a diminishing effect on pcpi.

Two ways of measuring changes in the oil market were developed. The oil/income ratio was developed to most accurately measure the effects of changes in the oil market in Oklahoma City. For comparing Oklahoma City with other cities and the nation as a whole, the average price of oil was used in the model. This allowed for a more versatile comparison. Both models gave us virtually the same results. An average increase of one dollar per barrel of oil is expected to cause a decrease of just over twelve dollars in pcpi.

The models developed to explain pcpi in Oklahoma City have one major drawback, they suffer from multicolliniarity. This is a problem inherent with the type of data being examined. It causes the variance of each of the parameters to be inflated. It also makes it difficult to determine the exact effects of each of the variables on pcpi because the estimated coefficients are imprecise. Unfortunately, little can be done to remedy this problem.

Pcpi in Oklahoma City has been lower than that of its neighboring cities of Dallas, Wichita, and Tulsa for the last thirty years. It has also remained, except for one brief period, below the national average. By applying the model developed for Oklahoma City to its surrounding cities, we got some idea as to whether they had the same variables effecting their pcpi. The model was particularly bad at estimating pcpi in

Dallas. Average oil price and employment were the only variables significant in Oklahoma City and Dallas. This indicates that Dallas has different variables driving its income.

The model did a better job of estimating Wichita pcpi, but still was lacking. Once again only two variables were significant. Moreover, because of multicolliniarity and poor specification, the model developed for Wichita did not make sense, putting a cap on pcpi of $18,200, lower than the current pcpi in many cities in the U.S. The determinants of pcpi in Wichita have some significant differences from those in Oklahoma City.

The model developed for Oklahoma City did a very good job of explaining pcpi in Tulsa. Tulsa and Oklahoma City appear to have fairly similar determinants of pcpi. This hints that the state the city is located in may have a significant effect on that city's pcpi. This could be due to state policies or outsiders perception of the state. Further research should be done on more cities to ascertain the determinants of pcpi in each one. A more specific and in depth model should be built for each city. By taking many cities individually and building their best model, it will be possible to look for variables that are relevant in all cities. Armed with a better understanding of the mechanics of pcpi at the city level, it might be possible to build a general model that can be applied to all cities.

## Appendix

Attachment 1: Original model

Dependent Variable: OKC PCPI
Method: Least Squares
Sample: 1969 1998
Included observations: 30

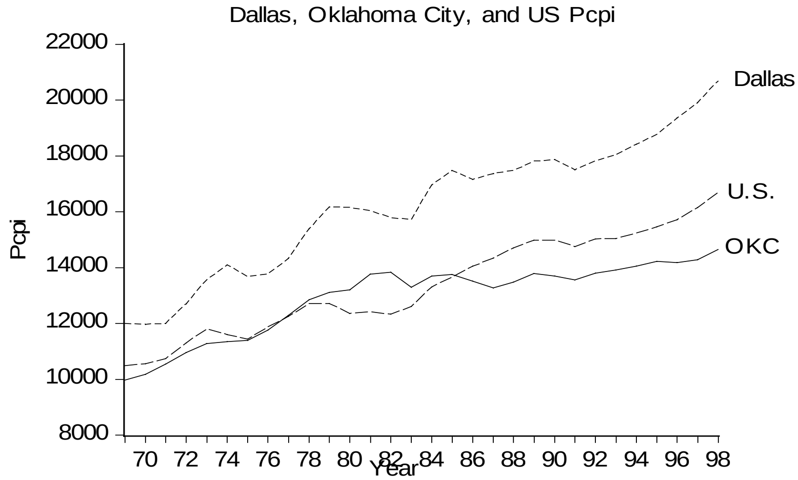
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -1807.405 | 1002.784 | -1.802388 | 0.0836 |
| Population | -0.006262 | 0.001679 | -3.729069 | 0.0010 |
| Employment | 0.062237 | 0.005720 | 10.88039 | 0.0000 |
| Employment^2 | -4.15E-08 | 4.39E-09 | -9.448189 | 0.0000 |
| Oil/Income Ratio | -81.81480 | 34.51646 | -2.370313 | 0.0258 |
| R-squared | 0.988635 | Mean dependent var | | 12920.79 |
| Adjusted R-squared | 0.986817 | S.D. dependent var | | 1335.957 |
| S.E. of regression | 153.3916 | Akaike info criterion | | 13.05488 |
| Sum squared resid | 588224.8 | Schwarz criterion | | 13.28841 |
| Log likelihood | -190.8232 | F-statistic | | 543.6959 |
| Durbin-Watson stat | 1.566542 | Prob(F-statistic) | | 0.000000 |

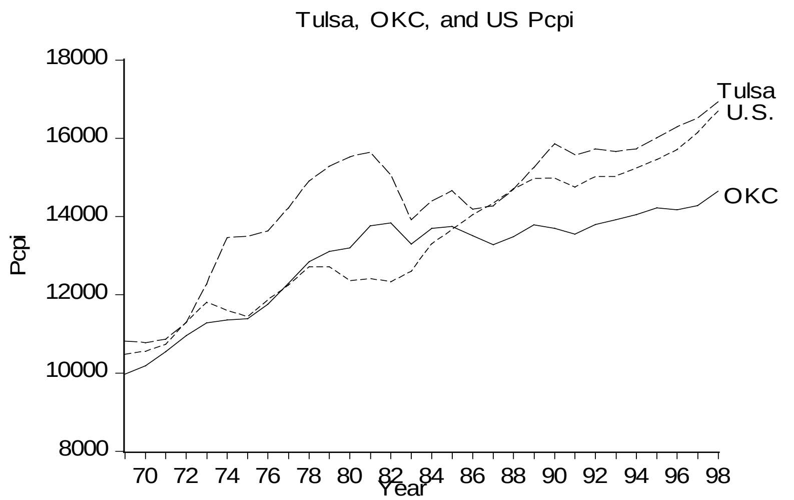
Attachment 2: Model modified for inter-city comparison

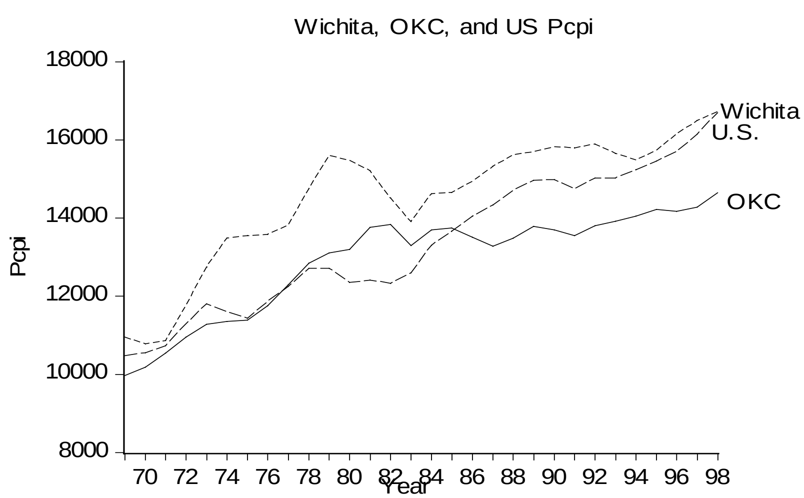
Dependent Variable: OKC PCPI
Method: Least Squares
Sample: 1969 1998
Included observations: 30

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -1702.859 | 1025.647 | -1.660277 | 0.1094 |
| Population | -0.007265 | 0.002039 | -3.563236 | 0.0015 |
| Employment | 0.065141 | 0.007205 | 9.041071 | 0.0000 |
| Employment^2 | -4.43E-08 | 5.61E-09 | -7.895761 | 0.0000 |
| Avg. Oil Price | -12.33652 | 5.909910 | -2.087429 | 0.0472 |
| R-squared | 0.988147 | Mean dependent var | | 12920.79 |
| Adjusted R-squared | 0.986251 | S.D. dependent var | | 1335.957 |
| S.E. of regression | 156.6514 | Akaike info criterion | | 13.09693 |
| Sum squared resid | 613491.5 | Schwarz criterion | | 13.33047 |
| Log likelihood | -191.4540 | F-statistic | | 521.0463 |
| Durbin-Watson stat | 1.298956 | Prob(F-statistic) | | 0.000000 |

# Attachment 3: Comparison of Regionla Pcpi

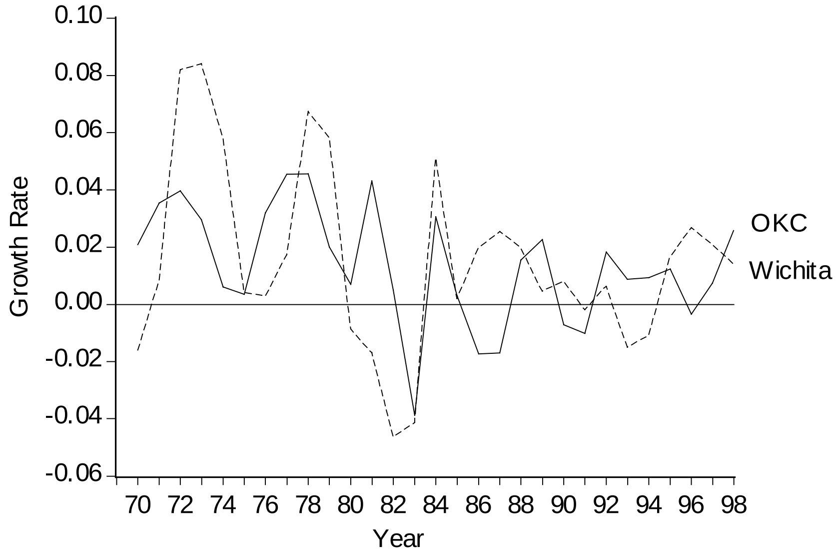


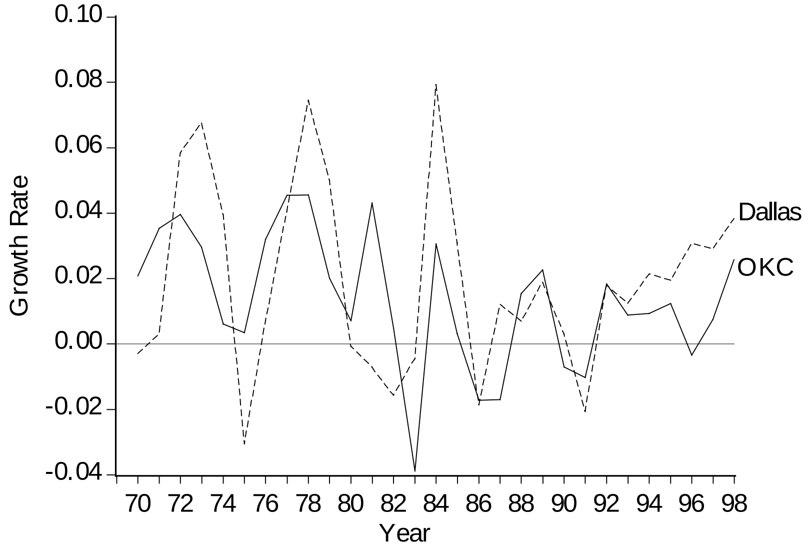



# Attachment 4

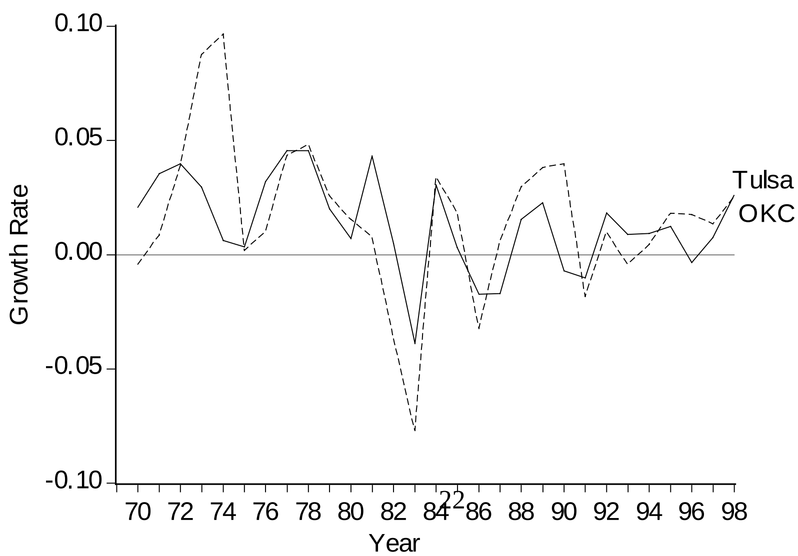
Growth: Wichita vs OKC




Growth: Dallas vs OKC




Growth: Tulsa vs OKC



Attachment 5: Mean and Standard Deviation of Growth Rates.

| | Mean | Std. Dev. |
|---|---|---|
| Oklahoma City | 0.0013549 | 0.02043 |
| Tulsa | 0.016112 | 0.033815 |
| Dallas | 0.01933 | 0.028592 |
| Wichita | 0.015199 | 0.032394 |
| United States | 0.016383 | 0.020896 |

Attachment 6: Formal test of Growth rates.

$H_0$: $\sigma_x^2 = \sigma_{okc}^2$
$H_1$: $\sigma_x^2 > \sigma_{okc}^2$

Decision Rule: Reject $H_0$ if $s_x^2/s_{okc}^2 > F_{29,29,0.05}$

Where x represents the city in being compared to Oklahoma City

Decision:

| | |
|---|---|
| $s_{Dallas}^2/s_{okc}^2 = 1.959 > 1.85$ | Reject $H_9$ |
| $s_{Tulsa}^2/s_{okc}^2 = 2.739 > 1.85$ | Reject $H_0$ |
| $s_{Wichita}^2/s_{okc}^2 = 2.514 > 1.85$ | Reject $H_0$ |

Conclusion: For Dallas, Wichita, and Tulsa, at a 5% significance level, we reject $H_0$ that the variance of the city's growth rate is equal to that of Oklahoma City's , in favor of $H_1$, that each of the city's growth rates have a larger variance than that of Oklahoma City.

Attachment 7: U.S. Model

Dependent Variable: US PCPI
Method: Least Squares
Sample: 1969 1998
Included observations: 30

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -3516.392 | 1561.546 | -2.251865 | 0.0330 |
| Employment | 0.000204 | 2.70E-05 | 7.565999 | 0.0000 |
| Employmen^2 | -4.92E-13 | 1.10E-13 | -4.479549 | 0.0001 |
| Avg. Oil Price | -28.58073 | 5.169063 | -5.529189 | 0.0000 |
| R-squared | 0.991669 | Mean dependent var | | 13374.95 |
| Adjusted R-squared | 0.990708 | S.D. dependent var | | 1788.104 |
| S.E. of regression | 172.3633 | Akaike info criterion | | 13.26065 |
| Sum squared resid | 772436.5 | Schwarz criterion | | 13.44748 |
| Log likelihood | -194.9098 | F-statistic | | 1031.667 |
| Durbin-Watson stat | 0.837326 | Prob(F-statistic) | | 0.000000 |

Attachment 8: Dallas Model

Dependent Variable: DALLAS PCPI
Method: Least Squares
Sample: 1969 1998
Included observations: 30

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 7843.238 | 329.2123 | 23.82425 | 0.0000 |
| Employment | 0.005267 | 0.000182 | 29.01542 | 0.0000 |
| Avg. Oil Price | 33.90789 | 9.733244 | 3.483719 | 0.0017 |
| R-squared | 0.969134 | Mean dependent var | | 16198.95 |
| Adjusted R-squared | 0.966847 | S.D. dependent var | | 2408.952 |
| S.E. of regression | 438.6182 | Akaike info criterion | | 15.09978 |
| Sum squared resid | 5194419. | Schwarz criterion | | 15.23989 |
| Log likelihood | -223.4966 | F-statistic | | 423.8721 |
| Durbin-Watson stat | 0.620432 | Prob(F-statistic) | | 0.000000 |

Attachment 9: Wichita Model

Dependent Variable: Wichita Pcpi
Method: Least Squares
Sample: 1969 1998
Included observations: 30

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 18206.30 | 1069.699 | 17.02002 | 0.0000 |
| Population | -0.058220 | 0.004679 | -12.44354 | 0.0000 |
| Employment | 0.084800 | 0.004245 | 19.97443 | 0.0000 |
| R-squared | 0.979075 | Mean dependent var | | 14521.49 |
| Adjusted R-squared | 0.977524 | S.D. dependent var | | 1671.307 |
| S.E. of regression | 250.5597 | Akaike info criterion | | 13.97991 |
| Sum squared resid | 1695064. | Schwarz criterion | | 14.12003 |
| Log likelihood | -206.6987 | F-statistic | | 631.6462 |
| Durbin-Watson stat | 1.234924 | Prob(F-statistic) | | 0.000000 |

Attachment 10: Tulsa Model

Dependent Variable: TULSAPCPI
Method: Least Squares
Sample: 1969 1998
Included observations: 30

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 3518.651 | 955.4373 | 3.682765 | 0.0011 |
| Population | -0.037304 | 0.002473 | -15.08700 | 0.0000 |
| Employment | 0.138861 | 0.007880 | 17.62175 | 0.0000 |
| Employment$^2$ | -1.09E-07 | 8.71E-09 | -12.50535 | 0.0000 |
| Avg. Oil Price | -12.48018 | 5.589391 | -2.232834 | 0.0348 |
| R-squared | 0.989459 | Mean dependent var | | 14432.08 |
| Adjusted R-squared | 0.987772 | S.D. dependent var | | 1723.594 |
| S.E. of regression | 190.5954 | Akaike info criterion | | 13.48920 |
| Sum squared resid | 908165.6 | Schwarz criterion | | 13.72273 |
| Log likelihood | -197.3379 | F-statistic | | 586.6519 |
| Durbin-Watson stat | 1.867266 | Prob(F-statistic) | | 0.000000 |

Attachment 11: Data Sources

1) PCPI, population, employment and oil production were obtained from the Regional Economic Information System, put out by the Bureau of Economic Analysis, a part of the U.S. Department of Commerce.

2) Average Oil Price was gotten off of the web page of the Oklahoma Corporation Commission.

3) The CPI used to transform all values into real values is from the Bureau of Labor Statistics.