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THE INFLATION AND OUTPUT-GAP TRADEOFF DEBATE REVISITED

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ABSTRACT

In this study we use four different measures of the US output to test the hypothesis of positive correlation between output-gap and wage inflation using the Phillips curve type models. We measure output gap using a constant natural level of output as well as the Kalman filter where natural level of output changes over time. Using the total real GDP or the service sector data the results did not support the hypothesis. However, we found an overwhelming evidence of positive correlation between output gap and wage inflation in the case of durable goods industries. Our results suggest that the requiem of Phillips curve may be premature.

JEL Classification: E24; E31

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1. INTRODUCTION AND OVERVIEW

The usual Phillips curve models relate inflation to some measure of aggregate economic activity, such as, the unemployment rate. Recent literature has also used the Phillips curve type models to forecast inflation (Atkenson and Ohanion 2001; Gordon 1977, 1998; Mathews and Kandilov 2002; Staiger, Stock and Watson 1997 and 1999; Grant 2002; Phelps and Zoga 1997, and others). In these versions of the Phillips curve, current unemployment rate or some other measure of current aggregate economic activity is used to forecast future changes in inflation rate. The underlying assumption is that there is some baseline unemployment rate, which is associated with a constant inflation rate. This baseline unemployment rate is referred to as the “Non-Accelerating Inflation Rate of Unemployment (NAIRU).” If the unemployment rate is above NAIRU, the inflation rate is expected to decrease, and vice versa (Friedman 1968; Phelps 1968; Stock and Watson 1999, and others). Using the Okun’s Law, transforming unemployment into output is straightforward (Grant 2002).[1]

NAIRU has a large number of followers. Alan Blinder, the former Vice Chairman of the Federal Reserve called it the “clean little secret” of empirical macroeconomics (Stock and Watson 1999; 293-4). Despite the fact that Akerlof (2002; 418-22) remains suspicious of the natural rate hypothesis, both on theoretical and empirical grounds, he (2002; 418) states that the Phillips curve is “Probably the single most important macroeconomic relationship…” Some opponents disagree with respect to the reliability of the tradeoff between inflation and unemployment; others question the ability of the Phillips curve type equations to forecast inflation (Atkenson and Ohanion 2000; Mankiw 2000, and others).

Despite the recent resurgence of interest in the Phillips curve, the lack of consensus on the efficacy of the relation combined with the importance of the policy implications warrant further investigation. To this end we use a simple variant of the Stock and Watson (1999) model to test the hypothesis of a positive correlation between output-gap and wage inflation. This study differs from the earlier studies in two important ways: (1) the manner in which we calculate the output-gap; (2) the data used in this study are aggregate economy-wide and disaggregated industry-level data.

To calculate the output-gap, we use two techniques to distinguish between the natural level of output and the observed level of output. First we use the textbook model in which the natural level of output is assumed to be constant. Then we apply the Kalman filter to estimate the natural level of output. Using the Kalman filter not only allows the natural output level to vary over time, it also captures technological shocks.

With regard to data set, we use four different classifications of the estimating variables for the U.S.; i.e., output, fulltime equivalent employee, and employee compensation. First we test the Phillips curve notion using data at the aggregate level for all three variables. Then we employ data that pertains to the services and manufacturing sectors. Next, the data set is disaggregated into durable and non-durable goods industries. Finally, durable and non-durable goods industries are further disaggregated at the two-digit industry-level.

Testing the Phillips curve equation under the four levels of aggregation has significant advantages. It provides added information on whether the notion is only valid at the aggregate level or it is also relevant at the sectoral level. Furthermore, additional knowledge may be gained by testing the notion at the durable and non-durable goods industries.

The plan of the paper is as follows: Section 2 presents the models used in this study; Sections 3 details the data used; Section 4 presents and analyzes results; Section 5 deals with the conclusions of the study.

2. MODEL

To test the hypothesis of a positive correlation between wage inflation and output-gap, we use a variant of the Stock and Watson (1999) model. We calculate the output-gap in two ways. First we use the textbook model in which the natural level of output is assumed to be constant. This technique is used in models (1) and (2) below. In models (3) and (4) we calculate the output-gap using the Kalman filter, which allows the natural output level to vary over time.

$$w_t - w_{t-1} = \beta_{1,0} + \beta_{1,1}\,(YGAP_{n,t}) + \varepsilon_{1,t} \qquad (1)$$

Where $\varepsilon_{1,t} = \rho_1 \varepsilon_{1,t-1} + \upsilon_{1,t}$

$$w_t - w_{t-1} = \beta_{2,0} + \beta_{2,1}\,(YGAP_{n,t}) + \beta_{2,2}\,(FTE_t) + \varepsilon_{2,t} \qquad (2)$$

Where $\varepsilon_{2,t} = \rho_2 \varepsilon_{2,t-1} + \upsilon_{2,t}$

And $YGAP_{n,t} = Y_t - Y_n$

The dependent variable, $w_t - w_{t-1}$, measures the wage inflation in a given data classification from year $t-1$ to t. Y_t is the gross product originating in a given data classification in year t as a percentage of gross domestic product, and Y_n is the natural level of gross product originating in a given data classification as a percentage of gross domestic product. In models where aggregate data are used, Y is the total real GDP. Thus model (1) is the generic text book Phillips curve equation. Both, in models (1) and (2), since Y_n is assumed to be constant through time, it is measured by a constant term (Stock and Watson 1999).

In model (2) we have added the fulltime equivalent employee (*FTE*), representing the labor market conditions, as an additional predictor of wage inflation. That is, productivity driven shifts in labor demand and/or shifts in labor supply may affect the wage rate. The link between wages and labor productivity is in compliance with the neoclassical hypothesis that wage growth may be due to a rise in labor productivity. If we observe an increase in wage inflation along with an increase in *FTE*, this would indicate that the labor demand shift dominates the labor supply shift. The converse would lead to the possible conclusion of decline in labor productivity. The movement of wage inflation and *FTE* in the opposite direction will indicate that the labor supply shift dominates the labor demand shift. In this instance, the implications for labor productivity are unclear.

To control for the labor market effects on wage rate, we include the fulltime equivalent employees, *FTE*, variable in models (2) and (4). The use of *FTE* combined with changes in wage inflation may gauge, albeit imperfectly, the effects of productivity changes on labor market.

Models (3) and (4) are based on the rationale that there is little evidence to believe that the natural level of output stays constant over time (Atkenson and Ohanian 2000; Mankiw 2000; Stock and Watson 1999). Thus, in models (3) and (4) we allow the natural level of output to vary.

$$w_t - w_{t-1} = \beta_{3,0} + \beta_{3,1}\,(YGAP_{e,t}) + \varepsilon_{3,t} \tag{3}$$

Where $$\varepsilon_{3,t} = \rho_3 \varepsilon_{3,t-1} + \upsilon_{3,t}$$

$$w_t - w_{t-1} = \beta_{4,0} + \beta_{4,1}\,(YGAP_{e,t}) + \beta_{4,2}\,(FTE_t) + \varepsilon_{4,t} \tag{4}$$

Where $$\varepsilon_{4,t} = \rho_4 \varepsilon_{4,t-1} + \upsilon_{4,t}$$

And $$YGAP_{e,t} = Y_t - Y_{e,t}$$

In models (3) and (4), $YGAP_{et}$, represents the expected output-gap. The output-gap $YGAP_{et}$, is the deviation of the actual output from the expected level of output where the expected level of output changes overtime. The expected level of output, $Y_{e,t}$, is calculated using the Kalman filter. The use of the Kalman filter to measure the output-gap is superior to the alternative where the natural level output is assumed to be constant. This is because the use of Kalman filter not only allows us to obtain a time variable natural level of output it also captures the effects of technological shocks.

Theoretically, the estimated values of $\beta_{i,1}$, for $i = 1, 2, 3, 4,$ are expected to be positive. In model (4), as in model (2), FTE_t measures the fulltime equivalent employees in a given data classification in year t. The estimated values of $\beta_{2,2}$ and $\beta_{4,2}$ may be positive or negative. If the labor demand curve shift dominates the labor supply curve shift, the values of $\beta_{2,2}$ and $\beta_{4,2}$ will be positive. The opposite will be true if the labor supply shifts dominate the labor demand shifts. ε_i, for $i = 1, 2, 3, 4,$ is the error term which may have a first order autoregressive structure and υ_j for $j = 1, 2, 3, 4,$ is a random error with zero mean and a constant variance.

3. DATA

The analysis in this study is based on data, at various levels of aggregations, for the period 1948-2000. We use the annual data on real GDP, gross product originating as a percentage of gross domestic product, employee compensation, and fulltime equivalent employees. In 2001, to compile the industry level data, the Bureau of Labor Statistics switched from the 1987 Standard Industrial Classification (SIC) system to the North American Industry Classification System (NAICS). Since the data from 2001 onward are not comparable with the earlier years, to preserve data consistency, we restrict our sample to the 1948-2000 period.[2] The data source is the U.S. Department of Commerce, Bureau of the Economic Analysis, Industry Economics Division. The URL is: www.bea.doc.gov.

4. RESULTS

To test for stationarity and cointegration, we use the Augmented Dickey-Fuller test, and Phillips-Ouliaris (1990) test, respectively. The results pointed out to the presence of cointegration between the wage inflation and the output measure. Furthermore, there also exists cointegration between the wage inflation, the output measure and fulltime equivalent employees in most data classifications. In situations where we could not reject the null hypothesis of no cointegration, the series were differenced to achieve stationarity.

We use the Maximum Likelihood Method to estimate the coefficients of the equations. The coefficient estimates of $YGAP_n$, $YGAP_e$ and FTE are standardized beta coefficients. The use of standardized beta estimates makes it easier to judge the relative importance of variables in a multiple regression model.

4.1. Results Using Data Aggregated at the US Level: Using aggregate data for the United States we present results of our estimations in Table 1. In model (1) and model (2), the output-gap is measured under the assumption that the natural level of output is constant overtime. In model (3) and model (4) we use the Kalman filter and the output-gap is measured by allowing the natural output level to vary over time.

Table 1
Total GDP Data: Maximum Likelihood Estimates
Dependent Variable: Wage Inflation

	Model 1	Model 2	Model 3	Model 4
Variable Name	Estimate (p-value)	Estimate (p-value)	Estimate (p-value)	Estimate (p-value)
$YGAP_n$	-0.0002	-0.569^b	-	-
	(0.992)	(0.026)		
$YGAP_e$	-	-	0.422^a	0.002
			(0.001)	(0.795)
FTE	-	0.576^b	-	0.823^a
		(0.026)		(0.000)
ε_{t-1}	0.349^b	0.292^c	0.51^a	0.752^a
	(0.012)	(0.062)	(0.000)	(0.000)
R^2	0.00	0.11	0.24	0.72
D-W	1.91	1.88	1.9	1.88
Z_ρ	-37.3^a	-39.97^a	-29.9^a	-21.7^b
Z_τ	-5.6^a	-5.6^a	-4.7^a	-3.9^b

Significance Levels: ^{a} = 1%, ^{b} = 5%, ^{c} = 10%.
D-W = Durbin-Watson statistic.
Z_ρ and Z_τ: Phillips-Ouliaris Test Statistic.

Using the total real GDP data, the results in Table 1 for model (1) and model (2) do not support the hypothesis that there is a positive correlation between the output-gap and wage inflation. That is, the results do not show that as output-gap increases wage inflation also increases. The coefficient estimates carry the theoretically “incorrect” signs, giving the implausible implication that as output-gap increases the wage inflation decreases.

It is important to point out that in model (1) and model (2) the output-gap is measured by assuming a constant natural level of output. Such an assumption could hardly be justified, as realistic, in a growing economy.

In models (3) and (4) we relax the assumption that the natural output level is constant overtime. Using the Kalman filter, the output-gap is measured by allowing the natural level of output to vary sequentially.

The coefficient estimate in model (3) strongly supports the hypothesis of a positive correlation between the output-gap and the wage inflation. The coefficient estimate of 0.422 implies that a one standard deviation increase in the output-gap leads to 0.42 standard deviation increase in the wage inflation.[3] The coefficient estimate is significant at the 1% level. However, as we include *FTE* as an additional variable in model (4) to account for wage inflation, the coefficient estimate for the output-gap becomes insignificant. The inclusion of *FTE* in model (4) renders the results of model (3) unreliable. However, the null hypotheses of no cointegration are rejected in all four models in Table 1. The values of Z_ρ and Z_τ are significant at the 5% or higher levels.[4]

4.2. Results for the US Services Sector: In this section we wish to test the Philips curve notion for the US services sector and in the next section for the US manufacturing sector. There are two reasons for this. (1) The results for the Phillips curve equation for the aggregate economy have been mixed. The support or rejection of the notion depends on whether we exclude or include the fulltime equivalent employee, *FTE*, variable in the estimating equation. (2) The notion of the Phillips curve has always been associated with aggregate economy and has not been applied to the different sectors of the economy. The application of the Phillips curve to a less aggregated classification may provide us better results than the economy as a whole. This may be due to a less objectionable nature of the production function as we move towards a less aggregated level.

The results for the US services sector are reported in Table 2 under models (1) through (4). The output-gap is measured in the same way as in Table 1. The coefficient estimate of $YGAP_n$ in model (1) is not significant at any reasonable level. In model (2) we add *FTE* as an additional explanatory variable to explain wage inflation. The inclusion of *FTE* into the model made the coefficient estimate of $YGAP_n$ significant only at the 10% level, but it produced a theoretically "incorrect" negative sign. Thus not much significance can be attached to these results.

Table 2
US Services Sector Data: Maximum Likelihood Estimates
Dependent Variable: Wage Inflation

	Model 1	Model 2	Model 3	Model 4
Variable Name	Estimate (p-value)	Estimate (p-value)	Estimate (p-value)	Estimate (p-value)
$YGAP_n$	0.11	-3.826[c]	-	-
	(0.714)	(0.077)		
$YGAP_e$	-	-	-0.256[b]	-0.324[b]
			(0.04)	(0.013)
FTE	-	3.936[c]	-	0.017[c]
		(0.056)		(0.094)
ε_{t-1}	0.675[a]	0.816[a]	-0.377[a]	-0.376[a]
	(0.000)	(0.000)	(0.008)	(0.008)
R^2	0.00	0.09	0.08	0.14
D-W	2.21	2.39	2.15	2.13
Z_ρ	-17.96[c]	-19.7	-66.2[a]	-65.2[a]
Z_τ	-3.7[b]	-3.8[b]	-10.6[a]	-10.2[a]

Significance Levels: [a] = 1%, [b] = 5%, [c] = 10%.
D-W = Durbin-Watson statistic.
Z_ρ and Z_τ: Phillips-Ouliaris Test Statistic.

We also tested for cointegration. When we used the Z_ρ value in model (1), we could only reject the null hypotheses of no conintegration at the 10% level (the critical value is 17.039, see Phillips and Ouliaris 1990, table Ib, page 189). Using the Z_ρ value, in model (2) we could not reject the null hypothesis of no cointegration. On the other hand, the use of Z_τ rejects the null hypotheses of no cointegration in both models at the 5% level (the critical value is 3.3654, see Phillips and Ouliaris 1990, table IIb, page 190).

In model (3) and model (4), Table 2, we calculate the output-gap using the Kalman filter, where the natural output level is not restricted to a constant and is allowed to vary from year to year. Here again, in the US services sector, the results do not support the Phillips curve hypothesis. The coefficient estimates, although significant, carry the theoretically "incorrect" negative signs.

Note, however, that when *FTE* is added to the model (2) and model (4), the coefficient estimates of output-gap increase in magnitude. This may reflect the nature of the services sector where increased demand may be met by overtime employment. As tempting as this explanation may seem, it has a limited scope. Beyond a certain point, firms may meet the increased demand by hiring and training additional workers.[5] The null hypotheses of no cointegration are rejected at the 1% level in all cases whether we use the Z_ρ value or the Z_τ value.

4.3. Results for the US Manufacturing Sector: In this sub-section of the paper we use data for the US manufacturing sector. The results are presented in Table 3.

Unlike the US service sector, the US manufacturing sector supports the Phillips curve hypothesis. In model (1) where *FTE* is not included in the estimating equation, the output-gap is significant only at the 10% level. In model (2), where *FTE* is included as an explanatory variable, not only the *FTE* coefficient is significant at the 1% level, it also raises the significance level of the coefficient of the output-gap to the 1% level.

In model (3) and model (4) the natural output level is allowed to vary over time. In this case, all the coefficient values of the explanatory variables are significant whether *FTE* is included or not in the estimating equation. However, when the assumption of the constant natural output is relaxed and *FTE* is added to the estimating equation, the explanatory power of the model increases as measured by the R^2. It increases from 0.68 in model (3) to 0.91 in model (4). In addition, all the coefficient estimates imply that as the output-gap increases, the wage inflation also increases. This result holds whether we use a constant natural level of output, as in models (1) and (2), or the Kalman filter, as in models (3) and (4). The results of the US manufacturing sector are in sharp contrast to the US service sector. The difference in the results may be partly due to the nature of the production function in the two sectors.

Table 3
US Manufacturing Sector Data: Maximum Likelihood Estimates
Dependent Variable: Wage Inflation

	Model 1	Model 2	Model 3	Model 4
Variable Name	Estimate (p-value)	Estimate (p-value)	Estimate (p-value)	Estimate (p-value)
$YGAP_n$	0.261^c	0.609^a	-	-
	(0.081)	(0.000)		
$YGAP_e$	-	-	0.565^a	0.171^a
			(0.000)	(0.001)
FTE	-	0.673^a	-	0.531^a
		(0.000)		(0.000)
ε_{t-1}	0.055	0.131	0.539^a	0.725^a
	(0.704)	(0.369)	(0.000)	(0.000)
R^2	0.06	0.32	0.68	0.91
D-W	1.86	1.92	1.8	1.89
Z_ρ	-50.5^a	-49.0^a	-29.0^a	-18.1
Z_τ	-7.2^a	-6.6^a	-4.7^a	-3.4^b

Significance Levels: ^{a} = 1%, ^{b} = 5%, ^{c} = 10%.
D-W = Durbin-Watson statistic.
Z_ρ and Z_τ: Phillips-Ouliaris Test Statistic.

As far as the no cointegration is concerned, the null hypotheses of no cointegration are rejected at the 1% level for models (1), (2) and (3) whether we use Z_ρ or Z_τ . However, in model (4), the null hypothesis of no cointegration is rejected only at the 5% level using the Z_τ value, but not using the Z_ρ value.

4.4. Results Using Durable and Non-durable Goods Industries Data: In this section we test the validity of the Phillips curve equation for the durable goods and non-durable goods industries. The rationale for this is that when we moved from an aggregate economy to manufacturing sector and services sector, the result for the Phillips curve notion improved substantially. Testing the notion by further dividing the manufacturing industry into durable and non-durable goods industries would give us additional insight into whether less aggregation would provide added strengthen the Phillips curve precept.

These results of the estimations for models (1), (2), (3) and (4) for the durable goods industries are presented in Table 4. Analogous results for the corresponding models for the non-durable goods industries are stated in Table 5.

The results of Table 4 and Table 5 strongly support the Phillips curve hypothesis in both durable and non-durable goods industries. The evidence shows the existence of a strong positive correlation between output-gap and the wage inflation. That is, as the gap between the natural level of output and the observed level of output increases, the wage inflation also increases. This outcome is independent of whether the natural output level is assumed to be constant or variable overtime. However, it is important to note that using the Kalman filter, in measuring the natural output level, shows a much stronger correlation between output-gap and wage inflation. Not only the values of coefficient estimates increase in magnitude, they also become significant at higher levels. Similarly, the use of Kalman filter in model (3) and model (4) increases the values of R^2.

Looking at the durable goods industries, model (1) in Table 4, the value of the coefficient estimate of $YGAP_n$, which is significant at the 5% level, implies that a one standard deviation increase in the output-gap, leads to an increase in the wage inflation by about 0.33 standard deviations. In model (2), when we introduce *FTE*, fulltime equivalent employees, as an additional explanatory variable the values of the coefficient estimate of $YGAP_n$ increase in magnitude as well as in significance. The magnitude of the coefficient increases from 0.327 to 0.569, and the significance level leaps from 5% to the 1% level. The addition of *FTE* in model (2) implies that a one standard deviation increase in the output-gap leads to a 0.569 standard deviation increase in the wage inflation.

Table 4
Durable Goods Data: Maximum Likelihood Estimates
Dependent Variable: Wage Inflation

	Model 1	Model 2	Model 3	Model 4
Variable Name	Estimate (p-value)	Estimate (p-value)	Estimate (p-value)	Estimate (p-value)
$YGAP_n$	0.327[b]	0.569[a]	-	-
	(0.024)	(0.001)		
$YGAP_e$	-	-	0.858[a]	0.936[a]
			(0.000)	(0.000)
FTE	-	0.551[a]	-	-0.117
		(0.001)		(0.395)
ε_{t-1}	0.043	0.208	0.122	0.078
	(0.767)	(0.15)	(0.402)	(0.596)
R^2	0.1	0.28	0.71	0.7
D-W	1.87	1.92	1.96	1.97
Z_ρ	-51.3[a]	-47.4[a]	-46.4[a]	-47.5[a]
Z_τ	-7.2[a]	-6.4[a]	-6.5[a]	-6.7[a]

Significance Levels: [a] = 1%, [b] = 5%, [c] = 10%.
D-W = Durbin-Watson statistic.
Z_ρ and Z_τ: Phillips-Ouliaris Test Statistic.

The coefficient estimate for $YGAP_e$, using model (3) where the natural output level changes over time, implies that a one standard deviation increase in the output-gap leads to an increase in the wage inflation of about 0.86 standard deviations. The estimated coefficient is significant at the 1% level. After controlling for the number of fulltime equivalent workers, *FTE*, in model (4) the estimated coefficient value increases in magnitude. The estimated value of $YGAP_e$ coefficient implies that a one standard deviation increase in the output-gap leads to an increase of 0.94 standard deviations in the wage inflation. In addition, using the Kalman filter to measure the output-gap in models (3) and (4) also leads to a substantial increase in the values of R^2. The increased values of R^2 imply that about 70% of the variations in the dependent variables are explained by the independent variables.

Table 5 presents the regression results for non-durable goods industries. Comparing these results with those of the durable goods industries, we find several differences between the two industries.

Table 5
Non-durable Goods Data: Maximum Likelihood Estimates
Dependent Variable: Wage Inflation

	Model 1	Model 2	Model 3	Model 4
Variable Name	Estimate (p-value)	Estimate (p-value)	Estimate (p-value)	Estimate (p-value)
$YGAP_n$	0.068	0.582[a]	-	-
	(0.729)	(0.001)		
$YGAP_e$	-	-	0.207[c]	0.189[c]
			(0.095)	(0.078)
FTE	-	0.838[a]	-	0.482[a]
		(0.000)		(0.000)
ε_{t-1}	0.294[b]	0.188	-0.473[a]	-0.357[b]
	(0.036)	(0.199)	(0.001)	(0.013)
R^2	0.00	0.37	0.06	0.36
D-W	2.02	1.88	1.82	1.63
Z_ρ	-38.9[a]	-46.5[a]	-65.2[a]	-57.4[a]
Z_τ	-5.8[a]	-6.6[a]	-13.0[a]	-9.2[a]

Significance Levels: [a] = 1%, [b] = 5%, [c] = 10%.
D-W = Durbin-Watson statistic.
Z_ρ and Z_τ: Phillips-Ouliaris Test Statistic.

In Table 5, the non-durable goods industries, the magnitudes of the estimates of the output-gap coefficients are smaller in comparison to the corresponding coefficients of the durable goods industries. The same is also true of the significance levels of the coefficients. There is another difference between the two types of industries. Unlike the durable goods industries, Table 4, model (4), the inclusion of *FTE* in the non-durable goods industries, Table 5, model (4), increases the coefficient estimates of *FTE*, the fulltime equivalent workers. The same is also true of the level of significance.

One possible explanation may be the differences in the ease of workers' entry into the two types of industries. Workers entry into the non-durable goods industries is relatively simpler than that of the durable goods industries. Another possible explanation may be the differences in requirement of the labor skills, differences in the amount of specialized investment on the part of workers between the two types of industries. Durable goods industries require higher level of skill and specialization compared to the non-durable goods industries. Yet another explanation may be the differences in the nature of the industries themselves; such as, differences in the production functions' requirement of various levels of labor and capital intensities.

As to the no cointegration hypothesis, the null hypothesis was rejected at the 1% level for both durable goods industries and the non-durable goods industries.

4.5. Results Using Two-Digit Industry-Level Data: Dividing the manufacturing sector into durable and non-durable goods industries has substantially added to the veracity of the Phillips curve notion. In this section we use data at an even lower level of aggregation to see if the Phillips curve equation finds further support at the two-digit industry level. A list of the industries used in this analysis along with corresponding SIC codes is provided in Table 6. To conserve space, we only present a summary of the results. Detailed results are available from the authors upon request.

Table 6
List of Industries (Industry description, 1987-SIC basis)

SIC	Industry Name
20	Food and Kindred Products
21	Tobacco Products
22	Textile Mill Products
23	Apparel and Other Products
24	Lumber and Wood Products
25	Furniture and Fixture
26	Paper and Allied Products
27	Printing and Publishing
28	Chemical and Allied Products
29	Petroleum and Coal Products
30	Rubber and Miscellaneous Plastics Products
31	Leather and Leather Products
32	Stone, Clay, and Glass Products
33	Primary Metal Products
34	Fabricated Metal Industries
35	Industrial Machinery and Equipment
36	Electrical and Electronic Equipment
371	Motor Vehicle and Equipment
372-379	Other Transportation Equipment
38	Instruments and Related Products
39	Miscellaneous and Related Products

Note: Data for Industrial Machinery and Equipment (SIC 35) prior to 1987 is for Machinery, except Electrical, which is the industry description according to the 1972 Standard Industrial Classification (SIC). SIC 24, 25, 32, 33, 34, 35, 36, 371, 372-379, 38, and 39 are categorized as Durable Goods Industries. Whereas, SIC 20, 21, 22, 23, 26, 27, 28, 29, 30, and 31 are categorized as Nondurable Goods Industries.

Using data for two-digit industries, we find further support for the hypothesis of a positive correlation between the output-gap and the wage inflation. The two-digit industries are composed of 11 durable goods industries and ten non-durable goods industries. Out of the 11 durable goods industries, none carries a negative significant estimate of $\beta_{1,1}$, the coefficient for the output-gap in model (1). To be more specific, in six of the 11 industries the standardized beta estimates of $\beta_{1,1}$ are positive and significant.

In four other industries the estimates are positive but not significant and in one industry the coefficient estimate has the theoretically "incorrect" negative sign and is insignificant.

When we control for *FTE* in model (2), five out of 11 durable goods industries carry the theoretically "correct" positive significant signs for $\beta_{2,1}$, the output-gap coefficient. Three of the 11 industries carry the "proper" positive signs but are insignificant. The two remaining industries carry theoretically "improper" negative signs but are insignificant. Here again the overall results imply that as the output-gap increases the wage inflation also increases.

On the other hand, the estimation results for the non-durable goods industries do not lend strong support for the Phillips curve hypothesis. The estimates of $\beta_{1,1}$ are positive significant for only four out of ten industries. Three industries have the theoretically "proper" positive signs for $\beta_{1,1}$, but are insignificant. The coefficient estimates for the three remaining industries have the theoretically "wrong" negative signs with only one being significant.

When we control for *FTE,* in model (2), support for the Phillips curve notion further deteriorates. The estimates of $\beta_{2,1,}$ the output gap coefficient, for eight industries out of ten, attain the theoretically "wrong" negative signs, with half being significant. Only two industries carry the "proper" positive and significant estimates for $\beta_{2,1}$. The implication of these findings is diametrically opposed to the teaching of the Phillips curve. That is, on average, for non-durable goods industries, after controlling for *FTE,* as output-gap increases wage inflation diminishes.

Interestingly, the coefficient of *FTE*, $\beta_{2,2}$, is positive and significant for 15 industries, spread evenly across the durable and the non-durable goods industries. Four industries carry positive but insignificant coefficients for $\beta_{2,2}$ (two durable goods industries and two non-durable goods industries). Two industries carry negative and insignificant coefficient for $\beta_{2,2}$ (both non-durable goods industries).

The regression results using the Kalman filter to measure the output-gap, models (3) and (4), further emphasize the distinction between the durable and the non-durable goods industries. For instance, in model (3) where the only independent variable is $YGAP_e$ the standardized coefficient estimates of $\beta_{3,1}$ for ten out of 11 durable goods industries are positive and significant and for only one durable goods industry the estimate is positive but insignificant. Whereas, for the non-durable goods industries, only five out of the ten industries carry positive and significant coefficient estimate of $\beta_{3,1.}$ Three industries carry positive but insignificant signs; one industry carries negative but significant sign, and one carries negative and insignificant sign.

The results of model (4) maintain similar distinctive pattern between the two groups of industries. The estimates for $\beta_{4,1}$, the output-gap coefficient, indicate that only three out of the ten non-durable goods industries carry significant and positive signs. Two carry positive but insignificant estimates, one carries negative and significant, and four carry negative but insignificant coefficient estimates. Looking at the durable goods industries, none carries the theoretically “improper” negative signs, significant or insignificant. In fact, six out of 11 carry positive and significant estimates for $\beta_{4,1}$. Five carry positive but insignificant coefficient estimates.

The coefficient estimates of *FTE* in model (4), $\beta_{4,2}$, carries positive and significant estimates for all industrial classifications, except SIC 34, 35, and 36, where the estimates are positive but insignificant, and SIC 371, where the estimate is negative and insignificant. These findings imply that, after allowing the natural output to vary overtime, the labor market effects on wage inflation are demand-driven.

5. CONCLUSION

The recent resurgence of interest in the Phillips curve analysis has produced lack of consensus on the relevance and efficacy of the relation. This revival of the Phillips curve hypothesis and the importance of its policy implications have been the primary motives for undertaking this study. Our study has several differences with the existing literature:

(1) The Data used in this analysis include 1948-2000 for the United States. The sample period is much longer than most studies and covers major ups and downs in economic activities.

(2) To estimate the Phillips curve notion, we calculated the output-gap using two different techniques. First we used the textbook approach in which we calculated the output-gap as the difference between current output and natural output with the latter remaining constant over time. Then we calculated the output-gap by allowing the natural output to vary over time. The sequential variation of natural output was obtained by using the Kalman filter. An additional advantage of using Kalman filter is that it also captures the effects of exogenous shocks.

(3) In estimating the Phillips curve equation, we first used data for the aggregate economy. Our regression results showed no support for the Phillips curve relation when we used the textbook approach to calculate the output gap. This was the case even when we included an additional explanatory variable, *FTE*, in the estimating equation. But

when we used the Kalman filter, the results strongly supported the Phillips curve hypothesis of a positive correlation between the output gap and wage inflation.

Next, we tested the hypothesis using data for the services sector and manufacturing sector. This was done to see if differences in the production functions between the sectors have any effect on the relevancy of the Phillips curve hypothesis. The results are intriguing. The service sector did not back up the hypothesis, irrespective of which models or the explanatory variables we used. In contrast to the services sector, the manufacturing sector supported the hypothesis. The differences in the results, between the two sectors, may be attributed to the difference in the production functions and the ease with which supplier and demander of labor can fill their requirements.

To test the hypothesis further, we divided the data of the manufacturing sector in to durable goods industries and non-durable goods industries. Interestingly enough, both types of industries effectively supported the hypothesis. However, the degree of support was much stronger in the durable goods industries than in the non-durable goods industries.

We continued our downward diversification of the industrial sector into two-digit industries. We found similar pattern of support at this low level of aggregation. The two-digit industries that are classified as durable goods industries, showed much stronger support than those that were designated as non-durable goods industries. In general, the magnitudes of the coefficient estimates and the degrees of significance were much more robust in the durable goods industries in comparison to the non-durable goods industries.

It seems reasonable to conclude that the differences in the results between the services sector and some of the non-durable goods industries and the rest of the manufacturing sector may partly be attributable to the differences in their production functions, differences in the labor skill level required, and differences in the workers' ease of entry into the workplace.

To sum up, to the best of our knowledge, the Phillips curve hypothesis has never been tested at such low level of aggregation. If future research supports our findings and pinpoints the production function differences among sectors, the Phillips curve may prove to be a "smart" macroeconomic policy tool that can target specific sectors of the economy.

Endnotes:

APPENDIX: This appendix provides descriptive statistics.

Total GDP

Variable	n	Mean	Std Dev	Minimum	Maximum
Real GDP	53	44494.78	21664.37	15511.50	92244.59
FTE	53	79298.08	22701.49	46784.00	125411.00
Wage Inflation	52	0.0710816	0.0301034	-0.0048131	0.1560862
Real GDP-Gap	52	18.1378856	1015.61	-2373.05	1961.28
d-FTE	52	1488.25	1608.87	-1810.00	4432.00
d-Wage Inflation	51	0.0014473	0.0340495	-0.0779221	0.0906849

U.S. Service Sector

Variable	n	Mean	Std Dev	Minimum	Maximum
Share-GDP	53	13.2683962	4.2629228	7.7680000	21.9250000
FTE	53	16154.43	9380.52	6157.00	37958.00
Wage Inflation	52	0.0920559	0.0257406	0.0314350	0.1535593
Share-GDP-Gap	52	0.0047495	0.2133203	-0.6120549	0.6014058

d-FTE	52	611.1730769	459.0929984	-76.00	1500.00
d-Wage Inflation	51	0.0012810	0.0210458	-0.0544728	0.0545733

U.S. Manufacturing Sector

Variable	n	Mean	Std Dev	Minimum	Maximum
Share-GDP	53	22.9633019	4.4670320	15.8670000	29.6180000
FTE	53	17881.64	1428.05	14368.00	20610.00
Wage Inflation	52	0.0574216	0.0469018	-0.0496864	0.1719582
Share-GDP-Gap	52	-3.20257E-17	0.6913807	-1.7633654	1.7976346
d-FTE	52	50.8076923	691.7470080	-1755.00	1228.00
d-Wage Inflation	51	0.0020655	0.0624064	-0.1511225	0.1803500

Durable Goods

Variable	n	Mean	Std Dev	Minimum	Maximum
Share-GDP	53	13.3516415	2.6486017	9.1330000	17.4010000
FTE	53	10454.25	1112.09	7494.00	12613.00
Wage Inflation	52	0.0600035	0.0609422	-0.0795185	0.2253687
Share-GDP-Gap	52	4.163336E-17	0.6645966	-1.8451154	1.8158846
d-FTE	52	51.2884615	535.1027512	-1241.00	1003.00
d-Wage Inflation	51	0.0028071	0.0821999	-0.2066510	0.2428024

Non-durable Goods

Variable	n	Mean	Std Dev	Minimum	Maximum
Share-GDP	53	9.6116604	1.9503399	6.7340000	13.58500
FTE	53	7427.40	351.6506319	6703.00	8003.00
Wage Inflation	52	0.0535693	0.0290424	-0.0144756	0.1256120
Share-GDP-Gap	52	1.120898E-17	0.1676310	-0.3802500	0.3887500
d-FTE	52	-0.4807692	172.1951117	-514.0000000	335.00000
d-Wage Inflation	51	0.0010660	0.0339774	-0.0646480	0.1037096

Notes:

1. All variables are in real terms.
2. *FTE* = Full-time Equivalent Employees
3. "*d*" in front of a variable indicates that the variable is in first-difference.
4. *Real GDP-Gap* represents the difference from its expected value, where expected value is calculated using the Kalman Filter.
5. *Share-GDP* = (Real Gross Product Originating in Sector *i*/*Real GDP*); for *i* = U.S. Service Sector, U.S. Manufacturing Sector, Durable Goods, Non-durable Goods.
6. *Share-GDP-GAP* represents the difference from its expected value, where expected value is calculated using the Kalman Filter.

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[1] Grant (2002) empirically verifies the relationship between employment and output. He states that "The estimates are robust to the alternative measures of the business cycle …"

[2] For further details, please visit: http://www.bls.gov/bls/naics.htm or http://www.census.gov/epcd/www/naics.html.

[3] Descriptive statistics of the data series total GDP, US service sector, US manufacturing sector, durable goods, and non-durable goods are presented in the Appendix to the study. Space limitation prohibits the presentation of descriptive statistics for the data disaggregated at the two-digit industry level. However, these are available from the authors.

[4] One of the questions we dealt with was the structural break. When the sample period is long, as is the case in this study, structural breaks detract the veracity of the findings. Thus, we tested for structural breaks using the Chow test. To no surprise, we found that structural breaks occurred around the mid-1970s. Recasting our analysis, using the R^2, the coefficient estimates, and their significance levels as yardsticks, we found that the pre 1977 data lent more support to the Phillips curve hypothesis than the post 1977 data. These findings are widely supported in the literature (see Gordon 1998). Please note, however, that the use of Kalman filter to measure the varying natural level of output captures the exogenous shocks. As a result it also takes care of the structural brakes. Please see Hamilton (1994; 372-402) for further details.

[5] We thank an anonymous referee for this point. We find similar result in model (2), Table 1.