Asymmetries in New Keynesian Phillips Curves: Evidence from US Cities

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Abstract

Studies of the relationship between national inflation rates and the output gap, as formalized in the New Keynesian Phillips Curve, ignore macroeconomic heterogeneity which exist in different parts of the country. This paper investigates differences in inflation and output across United States cities. The policy implications are difficult to ignore given differences in production across the country as a whole. Also of interest is identifying the median city-economy in the US. Thus when policy is implemented which city sees the greatest benefit of new policy? In addition to considering the standard Phillips relation between inflation and the output gap, I also consider the relationship between inflation and an index of wage costs as suggested in the literature. Preliminary results demonstrate a significant degree of heterogeneity across cities implying centralized policy prescriptions are helpful for some economies are harmful to others.

Keywords: Real interest parity condition, Transition countries, Unit root test, Structural breaks

JEL: E31, E43, F32, F41

Introduction

One of the fundamental policy relationships has been the Phillips Curve. In its earliest form, Phillips (1958) demonstrated the inverse relationship between wage inflation and the unemployment rate. This formulation was revised by Samuelson and Solow (1960) to the textbook version of unemployment rate and inflation. One of the key implications of this standard Phillips Curve is that, given an underlying deterministic economic structure, no policy maker can have both low inflation and unemployment contemporaneously. From this analysis came the theoretical underpinnings for the monetary policy loss function and the Taylor Rule, Taylor (19xx).

Simple Keynesian style business cycle use a national Phillips Curve relationship when constructing the aggregate supply curve. xxx

It is well established that over time rational expectations the Phillips Curve collapses. However, a key assumption of this literature is perfect price flexibility. To counter the rational expectations legitimate xxx several models with price stickiness have been introduced.

However, a shortcoming of this approach was to treat the entire economy homogenously. Put another way, centralized monetary policy is optimal for all of the economy's 'city-states'. In the past decade, or so, has come considerable evidence that responses to real and nominal shocks are asymmetric and heterogenous, particularly to prices. Parsely and Wei (199x) were the first to demonstrate differences across cities using disaggregated price series. Using panel methods, Cecchetti, Mark, and Sonora (2002) demonstrated that price convergence across US cities was highly persistent. More recently, for example, Chen and Devereux (2003), Sonora (2008) and Basher and Carrion-i-Silvestre (2009), numerous authors have found considerable differences in price convergence among US cities.

In the business cycle literature there is increasing evidence demonstrating asymmetric impacts of centralized monetary policy on region or city specific business cycles. Carlino and DaFina (1998, 1999a, 1999b), demonstrate a inter-regional and state business cycle heterogeneity across the eight Bureau of Economic Analysis (BEA) regions in the US. They identify three main sources of regional idiosyncratic responses to monetary policy: *i.* the mix of interest-sensitive industries; *ii.* mix of large and small firms; and *iii.* idiosyncratic banking regulations. Using semi-annual data Eyler and Sonora (2010) show considerable differences to monetary policy across US cities. Indeed, city-states face a monetary sub-optimal policy premium with a centralized monetary policy, especially when confronted by asymmetric shocks, see Lane (2000). These shocks further undermine regional macroeconomies if the shocks are moving in opposite directions.

Of course, contrary shocks are ameliorated when a central fiscal authority is in place, as in the US. Regions suffering from negative shocks receive transfers from others enjoying positive shocks.[1] Alternatively, regions whose economies are weighted heavily in a particular sector, see greater benefits from government spending in that particular sector, e.g. military spending.

This paper analyzes the impacts of these asymmetric shocks with New Keynesian Phillips Curve (NKPC) from 1969-2008. The model used is the NKPC derived in Galí and Gertler (1999) and, in its various manifestations, frequently used in the literature to model inflation dynamics. In general it models inflation as a function of expected inflation and cost or demand 'gap'. They employ the share of labor income and the output gap as explanatory variables in understanding inflation dynamics. They also include lagged inflation as a possible explanatory variable, to accommodate backward looking firms, the 'hybrid' NKPC.[2]

With quarterly US data they demonstrate a relatively high degree of price flexibility. However, Galí et al (2001) compare the euro area and the US and show the model fits European data better than with the US. The Galí et al (2001) paper and xxx (2009) are of the most interest to this paper as they examine inflation dynamics in monetary union. While Galí et al (2001) use pre-euro data, their sample does include about 15 years of a monetary union in Europe. Likewise, this paper treats individual cities as economic 'city-states' each with different underlying macroeconomic dynamics. Like the eurozone, each city's monetary policy is dictated by a single central bank, which, essentially, must treat the cities as, more or less, homogeneous.

This paper examines inflation dynamics in twenty-four US cities using city specific price and income data. Using real wages, as a proxy for marginal cost, and the output gap as explanatory variables I find considerable heterogeneity across US city inflation. Contrary to some of the literature, notably Galí et al (2001) I found the output gap to be better at explaining inflation than real wages. While there is considerable differences across cities, most of the estimates are line with the extant literature.

[1]This has been most glaring during the current Great Recession, particularly for those regions which underwent large real estate bubbles. Likewise, areas already in decline, for example the Great Lakes states, saw a worsening of their economies.

[2]There has been some debate about the robustness of these models. Rudd and Whelan (2005, 2007), who argue that this class of models cannot fully explain the importance of lagged inflation, nor do they capture role of future inflation in current inflation dynamics.

The remainder of the paper is as follows, in Section 1 we summarize the theoretical underpinnings of real interest rate parity; Section 2 discusses the data and provides some descriptive statistics; in Section 3 we outline the statistical tests and provide a summary of inflation expectations; finally Section 4 provides some summary remarks.

1 Theoretical Motivation

Naive Keynesian Phillips Curve

The so-called 'naive' Keynesian Phillips Curve (KPC) is easily derived from the more traditional Phillips curve and Okun's law. Write the Phillips curve as the inverse relationship between inflation and cycle unemployment as:

$$\pi_t - \pi_t^e = -\gamma(u_t - \bar{u}) + \epsilon_t \tag{1}$$

where u_t is unemployment rate, $\bar{u}$ is the natural rate, or NAIRU, of unemployment; π_t is the inflation rate; and $\bar{\pi}_t$ can alternatively be defined as an inflation target and/or the long run inflation rate. $u_t - \bar{u}$ is simply unemployment which results from business cycle fluctuations, cyclical unemployment.

Okun's law is the relationship between cycle unemployment and the output gap, defined as the percentage difference between current and potential output:

$$u_t - \bar{u} = -\delta\tilde{y}_t + \psi_t \tag{2}$$

where $\tilde{y}_t = \ln(y_t/\bar{y}_t)$ is the output gap, with y_t is real GDP and $\bar{y}_t$ is the long run level, or potential, real GDP. Combining equations (1) and (2) yields the textbook KPC

$$\pi_t = \pi_t^e + \alpha\tilde{y}_t + \nu_t \tag{3}$$

where $\alpha = \delta\gamma$ and $\nu_t = \epsilon_t + \psi_t \sim iid(0, \sigma^2)$ represents a cost shock. Alternatively, using the positive aggregate supply relationship between marginal costs and the output gap:

$$\widetilde{mc}_t = \kappa\tilde{y}_t, \kappa > 0 \tag{4}$$

equation (3) can be rewritten as

$$\pi_t = \pi_t^e + \mu\widetilde{mc}_t + \nu_t \tag{5}$$

where $\mu = \alpha\kappa$

With adaptive expectations we substitute $\pi_{t-1} = \pi_t^e$ to give us the naive KPC,

$$\pi_t = \pi_{t-1} + \alpha\tilde{y}_t + \nu_t. \tag{6}$$

'Modern' NKPC

The roots of the modern NKPC can be found in sticky price models introduced by Taylor's (1980) contract staggering model. In a monopolistically competitive market, firms face some costs of changing prices each period, small menu costs, monopoly profit maximization, or price 'contracts'. In an ideal setting we would have information about each firm, their price setting behavior and their time dependent pricing rules, is clearly nontractable at the aggregate level.

A simplification to this was proposed by Calvo (1983) assumes that in each period a firm has a fixed probability, $(1-\theta) \in (0,1)$ that it will change its price, and θ chance it will not. With this pricing rule, the probability is independent of the time elapsed since the last price change. The average time between each price revision is given by $1/(1-\theta)$ which simplifies the aggregation of prices as revisions are independent of the firms pricing history.

To derive the NKPC assume that firms are identical except for the value of their production and their pricing calender. If each firm faces a constant price elasticity of demand the overall price level is the weighted average of lagged price level and the profit maximizing reset price, p_t^*, thus

$$p_t = \theta p_{t-1} + (1-\theta)p_t^*. \tag{7}$$

with each price is the deviation from the steady state. The degree of price stickiness in this model is calibrated by θ as $\theta \to 1$ prices are perfectly flexible.

Firms set prices so as to minimize the loss (or maximize the profit) over the time in which the price is fixed. Define the loss function of the representative firm as the discounted loss over the pricing period

$$\ell(p_t) = \sum_{k=0}^{\infty} (\theta\beta)^k E_t(p_t - p_{t+k}^*) \tag{8}$$

where $\beta \in (0,1)$ is the discount factor. Differences are weighted by the discount factor and the probability of not changing the price. Minimizing the loss function, it can be shown that the optimal reset prices is given as the discounted flow of future optimal prices

$$p_t^* = (1-\theta\beta) \sum_{k=0}^{\infty} (\theta\beta)^k E_t(p_{t+k}^*). \tag{9}$$

If the price is given by the markup adjusted nominal marginal cost, $p_t = \mu + mc_t$, we get

$$p_t^* = (1-\theta\beta) \sum_{k=0}^{\infty} (\theta\beta)^k E_t(\mu + mc_{t+k}). \tag{10}$$

Converting prices to inflation and solving these equations (7) and (10) forward it can be shown that

$$\pi_t = \beta E_t \pi_{t+1} + \lambda \widetilde{mc}_t. \tag{11}$$

where $\lambda = \theta^{-1}(1-\theta)(1-\theta\beta)$ and $\widehat{mc}_t$ is the deviation from the long run real marginal cost $\widetilde{mc}_t = (\mu + mc_t - p_t) - \bar{mc}$. Alternatively, recalling equation (4), equation (11) can be written as

$$\pi_t = \beta E_t \pi_{t+1} + \kappa\lambda \widetilde{y}_t. \tag{12}$$

Equations (11) and (12) make up the basis of the empirical analysis.

Finally, the marginal cost gap can be derived from the profit maximization for the representative firm. Assuming production is Cobb-Douglas

$$Y_t = A_t K_t^{\omega_K} L_t^{\omega_L}$$

where A is a productivity, K is capital, L is labor, and the ωs are the share of input shares. Real marginal cost is derived from the period profit maximization problem as

$$mc^r = \frac{W_t}{P_t} \frac{1}{\partial Y / \partial L}$$

where W is the nominal wage and P is the price level. The above can be rewritten as

$$mc^r = \frac{W_t}{P_t}\frac{L_t}{Y_t}\frac{1}{\omega_L}, \tag{13}$$

Y/L is per capita income. Galí and Gertler (1999) use the share of labor income in non-farm income as their proxy for marginal cost, given by the above. ω_L is not available by city, so I simply use the real wage-per capita ratio.

2 Data

There are twenty three cities in sample, given limitations on data, all time series are annual, price level data is the annual average.[3] The United States (USA) as a whole is also included to observe city - national average differences. The sample is from 1969 – 2008, except for Miami which has price data available beginning in 1979. While using data with higher frequency would be preferable, semi-annual city income data is available only from 1990. Another complication with higher frequency data is that city CPI changes frequency and reporting periods over the sample.

Inflation and price level data are from the Bureau of Labor Statistics. City income and total and average annual wage data is from the Bureau of Economic Analysis. In the literature, one of the determinants of the wage gap is the share of labor income in the non-farm business sector, however this data is not available at the city level. I use the city hourly real wage for the marginal cost/share variable. To determine the average hourly wage for *all workers* I used the average annual wage divided by the average number of hours worked in each city in 2008. Annual hours worked was calculated by dividing the average annual wage by the average hourly wage in 2008, this data is available from 2007-2009. Average hourly wage is not available for Anchorage and San Francisco so I use the average pacific regional hourly wage for these cities.

The output and marginal cost gaps for the analysis are derived using a city specific Hodrick-Prescott (HP) filter each series. There has been some discussion over what the smoothing parameter, η, for annual data should be, most packages pre-specify a value of

[3]The cities (abbreviations) are: Anchorage, AK (ANC); Atlanta, GA (ATL); Boston, MA (BOS); Chicago, IL (CHI); Cinncinnati, OH (CIN); Cleveland, OH (CLE); Dallas-Ft. Worth, TX (DFW); Denver, CO (DEN); Detroit, MI (DET); Honolulu, HI (HON); Houston, TX (HOU); Kansas City, MO (KCM); Los Angeles, CA (LAX); Miami, FL (MIA); Milwaukee, WI (MIL); Minneapolis-St. Paul (MIN); New York City, NY (NYC); Philadelphia, PA (PHI); Pittsburgh, PA (PIT); Portland, OR (POR); San Diego, CA (SDO); San Francisco, CA (SFO); and Seattle, WA (SEA).

100 for annual data. Several authors, Maravall and del Río (2001) and Kim (2004) suggest $\eta \in [6, 14]$. Similarly, Ravn and Uhlig (1997) recommend the filter parameter be given by multiplying η with the fourth power of the observation frequency ratios, which yields a similarly low parameter. I split the difference in Maravell and del Río (2001) and Kim (2004) and set $\eta = 10$.

Table 1 displays the mean and standard deviation of inflation, total personal income, the annual per capita wage and average hourly wage for each of the cities, all statistics are in natural logs except inflation. Figures 1 – 3 show the annual city mean and standard deviation for the output gap, marginal cost gap, and inflation minus the US as a whole. As is shown, the city average can deviate by as much as 0.5% for short periods of time for each of the three series. Additionally, it appears that cost, output and inflation differences *are* falling as is witnessed by the decline of the standard deviation over the sample period.

Figure 4 displays the average log real wage and its standard deviation for the US over the period 1969-2008. As can be seen the highly inflationary late seventies and early eighties sharply reduced the real wage and it is only in 2006, or so, that it has recovered to pre-1975 levels. We also, a considerable degree of rea wage 'convergence' since 1979.

Table 2 displays the results of ADF unit root tests for each series. The output and wage gap refers to the HP detrended data discussed above. As can be seen the inflation and output gap series are stationary at the 10% level or better. Despite the break shown in Figure 4 the majority of the real wage series are also $I(0)$. The ocular estimator suggests an intercept and trend break in the series on average, in the early 1980s. I conducted a Zivot-Andrews test (Zivot and Andrews, 1992), Model 'C' which includes an intercept and slope break, to determine the dates of the break for each series. The break dates, are in the fifth column of 2 with the majority of the series breaking in 1985, the exceptions are Anchorage, Atlanta, Kansas City, and San Diego. The Zivot-Andrews unit root tests are not presented, but are available on request.

3 Statistical Methodology and Results

The standard method to estimating the Phillips Curve has been to simply use least squares of inflation on expected/lagged inflation and the output gap. Results of OLS regression on lagged inflation and the output gap frequently either produce statistically insignificant results and/or with estimated coefficients with the opposite sign as suggested by theory, see Galí and Gertler (1999). An additional problem arises when one considers the adaptive expectations version of the Phillips Curve in equation (6). In this case, prices are adjusted on past behavior and, thus, violate the pricing strategy employed by the profit maximizing firm over T future periods, as in equation (8). Additionally, unless all prices are adjusted every period, i.e. when $\theta = 1$, firms must perfectly anticipate changes in marginal costs, however, this is at odds with adaptive expectations.

For comparison purposes with the extant literature, I present results of the least squares regressions of the Keynesian Phillips curve for each city in Table 3. Both lagged and expected future inflation are used in the estimates. Each regression also includes a constant and the annual growth of oil prices (a cost shock), however, these estimates are not presented to minimize clutter. '*'s denote statistical significance at the 10% level or better. Cities identified with a '†' are cities where both inflation and the output and/or wage gap are statistically significant, at the 10% level or better, in at least one of the regressions. As with previous studies, some of the results are contrary to theory, the estimated coefficients on the gaps are negative, for example, Anchorage. Moreover, many of the results are not statistically significant.

Looking beyond the significance of the estimates, quickly perusing the results reveals that there is considerable differences across US cities with respect to the gap, though the coefficients on inflation are remarkably similar with most of the results falling in the 0.5 to 0.7 range.

Reduced Form Model

The inclusion of rational expectations in equations (11) and (12) implies that errors made in the forecast of expected inflation are uncorrelated with observations dated t and earlier. From these equations we can derive the reduced form model

$$[E_t(\pi_t - \alpha_1 \pi_{t+1} - \alpha_2 \widetilde{x}_t])z_t] = 0 \qquad (14)$$

where $\alpha_1 = \beta$ and $\alpha_2 = \lambda$, $\widetilde{x}$ alternatively is defined as the output gap or the real wage gap; and z_t is an orthogonal vector of instruments. The instruments used are two periods of lagged city specific inflation and the annual growth of oil prices. The orthogonality conditions are the basis for using GMM for estimating the model. In the literature, the marginal cost variable is contemporaneous to inflation. However, as suggested by equation (9) which shows that current optimal prices are a function of expected marginal costs, I employ an additional model where $\widetilde{x} = E_t mc_{t+1}$.

The results for these three models can be found in Table 4. $p-$values are in parenthesis, cites identified with a '†' are cities in which at least one specification is theoretically plausible and statistically significant. As can be seen, the GMM results using the output gap are consistently statistically significant and plausible. As in the OLS results, there is considerable heterogeneity of responses to both expected inflation and the output gap. As with the OLS results the expected inflation elasticity, α_1, is similar across all cities, falling between 0.95 to 1.05, although because $\alpha_1 = \beta$ estimates greater than 1.0 are theoretically inconsistent. However, inflation responses to the output gap vary considerably. The steepest statistically significant Phillips Curves, perhaps unsurprisingly, can be found in New York, with a gap elasticity, α_2, of 1.92. On the other hand, the shallowest is in Anchorage, with an elasticity of about 0.41.

When we consider the contemporaneous cost gap the results are less promising. All of the gaps are negative and statistically insignificant, though, as with the output gap, the inflation elasticities are similar, and close to those found with the output gap. On the other hand, the results for expected cost are largely positive, however, few are statistically significant. Those that are significant between roughly 1.7 and 8.0 (in St. Louis). The relatively large estimates are plausible as the marginal cost curve is given by ratio of the real wage weighted by per capita income.

Structural Model

Consider once again equations (11) and (12) which explicitly model the slope parameters in the reduced form models to be functions of both β and θ. Now we have a nonlinear econometric specification of the parameters.

As discussed in Galí and Gertler (1999), in small samples, the GMM estimates can be sensitive to the normalization of the orthogonality conditions. As in their paper, I use two different specifications of the model. The first structural model, Model 1, is given as

$$[E_t(\pi_t - \beta\pi_{t+1} - \theta^{-1}\varphi_t\widetilde{x}_t])z_t] = 0 \tag{15}$$

and the second, Model 2, is

$$[E_t(\theta\pi_t - \theta\beta\pi_{t+1} - \varphi_t\widetilde{x}_t])z_t] = 0 \tag{16}$$

where $\varphi = (1-\theta)(1-\theta\beta)$; $\widetilde{x}$ alternatively is defined as the output gap or the marginal cost gap; and z_t is a vector of instruments which are, once again, two periods of lagged city specific inflation and the annual growth of oil prices.

The structural GMM results can be found in Table 5. Again I identify successful models with a '†'. For example, consider Anchorage: Models 1 and 2 using the output gap as a measure of cost yield plausible estimates of the price adjustment parameter θ and the discount factor β. However, Model 1 with the wage gap, while yielding statistically significance estimates, is at odds with theory. The maximum and minimum statistically significant theoretically plausible estimates are underlined.

First we note that far more of the structural modes are successful than the reduced form versions, the majority of the cities have at least one successful model only Chicago, Denver, Miami, New York, Pittsburgh, San Diego, and St. Louis have no statistically significant successful models. Indeed, both New York and St. Louis produce theoretically plausible models, but one of the coefficient estimates were insignificant.

Turning our attention to differences across the various cities we see considerable asymmetries in the timing of price changes as well as discount factors. The estimates here yield, in general, $\theta \in (0.35, 0.60)$. This implies that price changes occur between 1.5 to 3.5 years depending on the city. While the first estimate is consistent with the extant literature, the later is a bit high. However, these results have considerable policy implications across cities.

Recall that as $\theta \to 1$ prices become perfectly flexible. It is interesting to view these results in term of the US city relative price convergence literature. Indeed, from this perspective, cities with higher price adjustment parameters should converge faster than those with closer to zero. There is some evidence when comparing these results with those found in, for example, Chen and Devereux (2003), Sonora (2008) or Basher and Carrion-i-Silvestre (forthcoming). There are several cities with relatively large adjustment parameters which also display relatively fast price convergence. For example, using the output gap Model 1 in Detroit has one of the largest price parameters and one of the faster convergence rates in Basher and Carrion-i-Silvestre (forthcoming). However, it must be noted that in the price convergence literature, price adjustment occurs in *relative* prices not univariate inflation or price levels.

Likewise, discount factors appear to be similarly asymmetric with some cities far more patient than others. In this context, more patience is manifested in great inflation expectation elasticity. The highest is in Anchorage with a statistically significant $\beta = 0.9999$ using Model 2 with an output gap. The least patient is Philadelphia with Model 2 and an output gap.

Galí and Gertler (1999) argued that the θ estimates might be biased upwards biasing the slope coefficients found in Table 4 downwards. First, is the how marginal cost is calculated as solely the function of the real wage. Though labor costs do account for the majority of cost to firms, the current paper relies on wages for costs. And secondly, to calculate real wage, city specific average number of hours worked in 2008 were backdated through the series, clearly labor supply and demand react to real wage changes over the course of the business cycle.

Nonetheless, they are less likely to be biased than when the economy as whole is estimated as individual city prices are reacting to local market conditions. With this in mind, it is important to note that the majority of the CPI is for nontraded goods and services – housing, transportation, etc. – which implies city Phillips Curves contain better information than an aggregated Phillips Curve.

A third version of the NKPC, called the hybrid NKPC, also includes a lagged inflation term in equation, however these results were not informative.[4]

4 Summary

The results presented demonstrate considerable heterogeneity of inflation dynamics across US cities. Moreover, the city-specific output gap is generally better suited to describe inflation for the period.

The results presented here imply that designing optimal monetary policy is quite challenging as each city will respond differently to monetary shocks. While this is challenging for an economy with centralized fiscal policy, the problem is compounded by other single currency areas which face decentralized fiscal authorities.

[4]Results are available on request.

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Tables

Table 1: **Descriptive Statistics**

	Inflation		Total Income		Per Capita Wage		Mean Real Wage	
	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
ANC	4.135	3.062	22.339	0.897	10.147	0.460	3.200	0.052
ATL	4.610	3.018	24.591	1.061	9.950	0.628	2.913	0.117
BOS	4.853	2.672	25.071	0.837	10.035	0.676	3.094	0.137
CHI	4.660	2.977	25.729	0.755	10.042	0.580	3.077	0.077
CIN	4.608	3.046	24.068	0.798	9.917	0.557	2.997	0.069
CLE	4.697	3.295	24.302	0.655	9.962	0.532	2.964	0.060
DEN	4.980	3.445	24.129	0.973	9.994	0.608	3.058	0.072
DET	4.552	3.133	25.017	0.682	10.093	0.539	3.159	0.056
DFW	4.657	3.394	24.867	1.017	9.963	0.624	2.909	0.107
HON	4.650	2.965	23.357	0.775	9.881	0.556	2.991	0.052
HOU	4.563	3.459	24.829	1.000	10.018	0.603	2.883	0.107
KCM	4.515	3.078	23.991	0.811	9.903	0.568	2.948	0.080
LAX	4.785	3.062	25.940	0.815	10.037	0.587	3.093	0.065
MIA	3.423	2.876	24.886	0.968	9.875	0.594	3.689	1.597
MIL	4.647	3.263	23.905	0.730	9.919	0.551	2.982	0.076
MIN	4.750	3.093	24.524	0.889	9.974	0.597	3.070	0.084
NYC	4.828	2.356	26.541	0.775	10.143	0.657	3.106	0.126
PHI	4.692	2.739	25.253	0.766	9.985	0.602	3.012	0.085
PIT	4.695	2.934	24.386	0.669	9.810	0.549	2.985	0.056
SFO	4.668	3.249	23.923	0.915	9.918	0.576	2.970	0.068
SDO	5.348	3.534	24.328	0.978	9.913	0.607	3.105	0.082
SEA	4.872	3.361	24.494	0.961	10.018	0.608	3.162	0.078
SFO	4.857	3.168	25.083	0.867	10.136	0.651	2.985	0.123
STL	4.480	3.077	24.447	0.748	9.926	0.560	2.951	0.073
USA	4.697	2.855	28.957	0.833	9.895	0.583	2.883	0.078

Table 2: **Unit Root Tests**

	π	Output Gap	Wage Gap	Break Year
ANC	-2.872*	-6.459**	-3.763**	1986
ATL	-4.444**	-3.570**	-2.960**	1980
BOS	-3.870**	-3.798**	-3.617**	1985
CHI	-3.091**	-4.202**	-2.990**	1985
CIN	-2.819*	-3.793**	-2.837*	1985
CLE	-3.208**	-3.608**	-3.386**	1985
DEN	-2.647*	-3.195**	-2.749*	1985
DET	-3.351**	-3.990**	-3.083**	1985
DFW	-2.627*	-2.894*	-2.627*	1985
HON	-3.421**	-3.310**	-3.219**	1985
HOU	-2.874*	-3.612**	-2.750*	1985
KCM	-2.987**	-4.064**	-2.396	1979
LAX	-3.045**	-3.735**	-3.075**	1985
MIA	-3.206**	-4.964**	-5.377**	1980
MIL	-2.941**	-3.966**	-3.346**	1985
MIN	-3.944**	-3.468**	-2.563	1985
NYC	-4.879**	-4.333**	-3.847**	1985
PHI	-4.463**	-5.049**	-3.918**	1985
PIT	-3.325**	-4.740**	-2.651*	1985
POR	-3.191**	-2.956**	-2.717*	1985
SDO	-3.003**	-4.184**	-2.629*	1979
SEA	-3.346**	-3.587**	-3.120**	1985
SFO	-4.014**	-4.028**	-3.601**	1985
STL	-2.717**	-3.229**	-2.861*	1985
USA	-3.140**	-3.916**	-2.974**	1985
Energy	-3.938**			

Notes: "*" and "**" denote rejection of a unit root at the 10% and 5% level respectively. Break is the year of an intercept and slope break using Zivot-Andrews' Model 'C'.

Table 3: **OLS Regressions**

	Lagged Inflation				Expected Future Inflation			
	Output Gap		Wage Gap		Output Gap		Wage Gap	
	π	Gap	π	Gap	π	Gap	π	Gap
ANC†	0.611*	0.005	0.573*	-0.086	0.622*	0.213*	0.621*	-0.563*
	(0.000)	(0.468)	(0.000)	(0.809)	(0.000)	(0.001)	(0.000)	(0.001)
ATL†	0.668*	0.358*	0.617*	-0.169	0.580*	0.040	0.613*	0.206
	(0.000)	(0.003)	(0.000)	(0.881)	(0.000)	(0.832)	(0.000)	(0.383)
BOS	0.561*	0.164	0.543*	-0.088	0.461*	0.191	0.444*	-0.248
	(0.000)	(0.113)	(0.000)	(0.729)	(0.000)	(0.253)	(0.001)	(0.346)
CHI	0.616*	0.194	0.654*	0.144	0.588*	0.161	0.594*	-0.022
	(0.000)	(0.154)	(0.000)	(0.168)	(0.000)	(0.449)	(0.000)	(0.935)
CIN	0.618*	-0.057	0.638*	0.154	0.602*	-0.033	0.605*	0.136
	(0.000)	(0.597)	(0.000)	(0.181)	(0.000)	(0.887)	(0.000)	(0.606)
CLE	0.625*	0.078	0.644*	0.078	0.582*	0.056	0.580*	-0.125
	(0.000)	(0.355)	(0.000)	(0.291)	(0.000)	(0.818)	(0.000)	(0.667)
DEN	0.651*	0.038	0.641*	-0.072	0.641*	0.268	0.636*	-0.095
	(0.000)	(0.409)	(0.000)	(0.673)	(0.000)	(0.132)	(0.000)	(0.742)
DET†	0.610*	0.396*	0.566*	0.031	0.537*	-0.065	0.519*	-0.014
	(0.000)	(0.002)	(0.000)	(0.424)	(0.000)	(0.671)	(0.000)	(0.949)
DFW†	0.598*	0.033	0.619*	0.080	0.573*	0.353*	0.549*	-0.001
	(0.000)	(0.400)	(0.000)	(0.261)	(0.000)	(0.035)	(0.000)	(0.998)
HON†	0.641*	-0.075	0.692*	0.180*	0.665*	0.557*	0.619*	-0.385
	(0.000)	(0.659)	(0.000)	(0.079)	(0.000)	(0.006)	(0.000)	(0.174)
HOU	0.641*	-0.133	0.630*	0.125	0.671*	0.379*	0.580*	-0.343
	(0.000)	(0.934)	(0.000)	(0.108)	(0.000)	(0.000)	(0.000)	(0.105)
KCM	0.559*	0.057	0.582*	0.111	0.512*	0.100	0.521*	0.072
	(0.000)	(0.407)	(0.000)	(0.279)	(0.000)	(0.709)	(0.000)	(0.813)
LAX†	0.559*	0.190	0.556*	-0.092	0.508*	0.413*	0.484*	-0.122
	(0.000)	(0.140)	(0.000)	(0.748)	(0.000)	(0.043)	(0.001)	(0.599)
MIA†‡	0.761*	-0.139	0.784*	0.132	0.620*	0.563*	0.563*	-0.194
	(0.000)	(0.811)	(0.000)	(0.166)	(0.000)	(0.003)	(0.004)	(0.460)
MIL†	0.653*	-0.055	0.697*	0.201	0.629*	0.374*	0.627*	-0.130
	(0.000)	(0.613)	(0.000)	(0.063)	(0.000)	(0.084)	(0.000)	(0.618)
MIN†	0.626*	0.477*	0.589*	-0.224	0.578*	0.340	0.612*	0.320
	(0.000)	(0.019)	(0.000)	(0.886)	(0.000)	(0.199)	(0.000)	(0.237)

Table 3: **OLS Regressions(Cont.)**

	Lagged Inflation				Expected Future Inflation			
	Output Gap		Wage Gap		Output Gap		Wage Gap	
NYC	0.637*	-0.023	0.641*	0.028	0.603*	0.177	0.583*	-0.091
	(0.000)	(0.581)	(0.000)	(0.409)	(0.000)	(0.206)	(0.000)	(0.662)
PHI	0.536*	-0.085	0.540*	0.042	0.455*	0.307	0.438*	0.063
	(0.000)	(0.643)	(0.000)	(0.400)	(0.000)	(0.255)	(0.001)	(0.858)
PIT†	0.648*	-0.262	0.662*	0.178*	0.562*	0.349*	0.540*	-0.284
	(0.000)	(0.948)	(0.000)	(0.050)	(0.000)	(0.048)	(0.000)	(0.141)
POR†	0.590*	0.027	0.620*	0.104	0.619*	0.477*	0.566*	-0.199
	(0.000)	(0.444)	(0.000)	(0.264)	(0.000)	(0.004)	(0.000)	(0.425)
SDO†	0.572*	0.187	0.625*	0.110	0.575*	0.533*	0.546*	-0.270
	(0.000)	(0.167)	(0.000)	(0.241)	(0.000)	(0.006)	(0.000)	(0.322)
SEA†	0.574*	0.046	0.563*	-0.092	0.542*	0.377*	0.522*	-0.056
	(0.000)	(0.364)	(0.000)	(0.729)	(0.000)	(0.004)	(0.000)	(0.809)
SFO†	0.578*	0.142	0.518*	-0.282	0.540*	0.259*	0.506*	-0.318
	(0.000)	(0.146)	(0.000)	(0.955)	(0.001)	(0.097)	(0.002)	(0.286)
STL	0.604*	0.073	0.633*	0.154	0.560*	0.263	0.575*	0.215
	(0.000)	(0.400)	(0.000)	(0.170)	(0.000)	(0.418)	(0.000)	(0.501)
USA	0.613*	0.057	0.641*	0.115	0.577*	0.346	0.564*	-0.007
	(0.000)	(0.369)	(0.000)	(0.191)	(0.000)	(0.109)	(0.000)	(0.980)

Notes: Constant term and oil inflation are not presented to minimize clutter, results available on request. $p-$values are in parenthesis. Cities identified with a '†' are cities where *both* inflation and the gap and/or the *mpc* are statistically significant, at the 10% level or better, in at least one of the regressions. ‡Miami sample begins in 1979. '*'s denote estimates of the gap parameter which are significant at the 10% level or better.

Table 4: **Reduced Form GMM Regressions**

	Output Gap		Wage Gap		Expected Wage Gap	
	π	Gap	π	MC	π	MC
ANC†	0.983***	0.406***	1.029***	-1.424***	1.235***	-1.180
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.180)
ATL	0.954***	0.437	0.948***	-0.346	1.017***	1.788***
	(0.000)	(0.440)	(0.000)	(0.627)	(0.000)	(0.000)
BOS	0.999***	0.469	0.995***	-0.547	1.021***	-0.072
	(0.000)	(0.161)	(0.000)	(0.132)	(0.000)	(0.928)
CHI	1.049***	1.441**	0.954***	-0.510	0.966***	0.250
	(0.000)	(0.031)	(0.000)	(0.539)	(0.000)	(0.805)
CIN	1.011***	1.499*	1.003***	-1.590	0.996***	0.353
	(0.000)	(0.054)	(0.000)	(0.163)	(0.000)	(0.648)
CLE	0.932***	0.384	0.943***	-0.866	0.965***	0.524
	(0.000)	(0.546)	(0.000)	(0.190)	(0.000)	(0.424)
DEN	0.989***	2.000	0.985***	-1.219	1.000***	0.064
	(0.000)	(0.329)	(0.000)	(0.291)	(0.000)	(0.945)
DET	0.942***	0.613	0.949***	-0.996	1.008***	2.531***
	(0.000)	(0.262)	(0.000)	(0.218)	(0.000)	(0.003)
DFW	1.088***	1.202***	0.919***	-0.698	0.966***	0.368
	(0.000)	(0.009)	(0.000)	(0.208)	(0.000)	(0.563)
HON	0.956***	0.472	0.910***	-0.882	0.944***	0.088
	(0.000)	(0.181)	(0.000)	(0.230)	(0.000)	(0.905)
HOU	1.029***	0.580**	0.992***	-0.879	1.047***	-0.621
	(0.000)	(0.036)	(0.000)	(0.044	(0.000)	(0.199)
KCM	1.034***	8.022	1.055***	-2.868	0.973***	-1.274
	(0.001)	(0.492)	(0.000)	0.401	(0.000)	(0.606)
LAX†	0.979***	1.061*	0.955***	-0.644	0.972***	0.732*
	(0.000)	(0.073)	(0.000)	0.271	(0.000)	(0.085)
MIA‡	1.016***	0.785***	0.977***	-1.454	1.189***	1.918***
	(0.000)	(0.000)	(0.000)	0.019	(0.000)	(0.001)
MIL	1.012***	1.272**	0.963***	-1.599	0.965***	-1.194
	(0.000)	(0.011)	(0.000)	0.051	(0.000)	(0.301
MIN	0.942***	0.288	0.971***	-0.019	1.026***	2.267***
	(0.000)	(0.659)	(0.000)	0.976	(0.000)	(0.001)

Table 4: **Reduced Form GMM Regressions (Cont.)**

	Output Gap		Wage Gap		Expected Wage Gap	
	π	Gap	π	Gap	π	Gap
NYC	1.047***	1.923**	0.996***	-0.907	0.995***	0.268
	(0.000)	(0.042)	(0.000)	0.324	(0.000)	(0.735)
PHI	0.889***	4.486	0.967***	-0.655	1.009***	1.541
	(0.000)	(0.114)	(0.000)	0.708	(0.000)	(0.500)
PIT	1.023***	1.033**	1.057***	-1.346	0.953***	-0.486
	(0.000)	(0.028)	(0.000)	0.011	(0.000)	(0.203)
POR	1.010***	1.120***	0.913***	-2.660	0.961***	0.170
	(0.000)	(0.001)	(0.000)	0.023	(0.000)	(0.830)
SDO	1.026***	1.649**	0.973***	-2.470	0.975***	-2.103
	(0.000)	(0.013)	(0.000)	0.134	(0.000)	(0.425)
SEA†	1.020***	0.863***	0.889***	-0.171	0.955***	0.697*
	(0.000)	(0.004)	(0.000)	0.722	(0.000)	(0.069)
SFO	0.927***	0.090	0.914***	-0.230	1.040***	1.884***
	(0.000)	(0.846)	(0.000)	0.629	(0.000)	(0.002)
STL	1.020***	3.737	1.003***	-0.988	1.010***	8.476*
	(0.000)	(0.226)	(0.000)	0.481	(0.000)	(0.087)
USA	1.031***	1.228**	0.957***	-0.976	0.994***	0.319
	(0.000)	(0.039)	(0.000)	0.231	(0.000)	(0.665)

Notes: $p-$values are in parenthesis. ‡Miami sample begins in 1979. ***, **, and * represent rejection of the null hypothesis at the 1%, 5%, and 10% level respectively. Cities identified with a '†' are cities where estimates in at least one model are statistically significant and with estimates which conform to theory, $\beta < 1$.

Table 5: **Structural GMM Regressions**

	Output Gap				Marginal Cost Gap			
	Model 1		Model 2		Model 1		Model 2	
	θ	β	θ	β	θ	β	θ	β
ANC†	0.5374***	0.9828***	$\underline{0.5189}$***	$\underline{0.9999}$***	0.3864***	1.0516***	1.0352	80.68
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.171)	(0.142)
ATL†	0.5305**	0.9539***	0.3516***	0.9849***	0.1456	1.0409*	-0.2221	-0.2168
	(0.016)	(0.000)	(0.004)	(0.000)	(0.990)	(0.064)	(0.614)	(0.509)
BOS†	0.5109***	$\underline{0.9989}$***	0.2974***	1.1702***	0.8809***	0.9715***	0.5024***	1.0236***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.000)
CHI	3.0111***	1.0486***	0.2839***	1.0628***	$\underline{0.3594}$***	1.0342***	0.1748	1.1687***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.143)	(0.000)
CIN†	3.1589***	1.0111***	2.8991***	1.0269***	1.0574	1.0324***	0.3451**	0.9534***
	(0.002)	(0.000)	(0.003)	(0.000)	(0.817)	(0.000)	(0.037)	(0.000)
CLE†	$\underline{0.5562}$**	0.9321***	0.3299***	0.9860***	27.419	0.9213***	0.3633**	0.9253***
	(0.047)	(0.000)	(0.000)	(0.000)	(0.743)	(0.000)	(0.030)	(0.000)
DEN	3.7649	0.9890***	3.5499	0.9967***	2.1265	1.0432	$\underline{0.1653}$***	1.2685***
	(0.142)	(0.000)	(0.138)	(0.000)	(0.594)	(0.000)	(0.393)	(0.001)
DET†	0.4745***	0.9417***	0.2603**	0.8653***	-0.4394	0.9503***	$\underline{0.7056}$**	0.9367***
	(0.003)	(0.000)	(0.025)	(0.000)	(0.800)	(0.000)	(0.042)	(0.000)
DFW†	2.6803***	1.0880***	2.3193***	1.0132***	1.1908***	0.9727***	0.6072**	0.8870***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.015)	(0.000)
HON†	2.0224***	0.9563***	0.2970***	0.9075***	1.1067	0.9384***	-0.0955	1.0005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.451)	(0.000)	(0.741)	(0.011)
HOU†	0.4708***	1.0287***	0.4620***	0.9866***	4.7195	0.9499***	0.1943	1.5969
	(0.000)	(0.000)	(0.000)	(0.000)	(0.135)	(0.000)	(0.337)	(0.018)
KCM	9.6244	1.0340***	9.5143	1.0340***	-0.2983	1.0896***	-0.0045	-0.3000
	(0.385)	(0.001)	(0.387)	(0.001)	(0.963)	(0.000)	(0.970)	(0.994)
LAX†	$\underline{0.3739}$***	0.9789***	0.2980***	0.9694***	1.5912	0.9508***	0.4832***	0.9620***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.338)	(0.000)	(0.003)	(0.000)
MIA‡	0.4215***	1.0156***	0.4161***	1.0212	-1.7892	$\underline{0.9941}$***	0.4138***	1.0185***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.797)	(0.000)	(0.003)	(0.000)
MIL†	2.9049***	1.0119***	2.3503***	1.0022***	1.7651*	0.9475***	0.4755**	$\underline{0.9768}$***
	(0.000)	(0.000)	(0.002)	(0.000)	(0.094)	(0.000)	(0.048)	(0.000)
MIN†	0.6007*	0.9424***	0.1898*	1.0999***	1.2859	0.9716***	1.2859	0.9716***
	(0.093)	(0.000)	(0.072)	(0.000)	(0.312)	(0.000)	(0.312)	(0.000)

Table 5: **Structural GMM Regressions (Cont.)**

	Output Gap				Marginal Cost Gap			
	Model 1		Model 2		Model 1		Model 2	
	θ	β	θ	β	θ	β	θ	β
NYC	3.5192***	1.0474***	3.4632***	1.0498***	-14.4198	1.0131***	0.2100	0.9844***
	(0.002)	(0.000)	(0.002)	(0.000)	(0.195)	(0.000)	(0.226)	(0.000)
PHI†	7.0127**	<u>0.8886</u>***	<u>0.1237</u>**	<u>0.8603</u>***	2.5816	0.9725***	0.0098	1517.38?
	(0.058)	(0.000)	(0.042)	(0.000)	(0.836)	(0.000)	(0.998)	(0.997)
PIT	0.3741***	1.0229***	0.3683***	1.0208	1.0185	1.0231	-0.5163	5.851
	(0.000)	(0.000)	(0.000)	(0.000)	(0.929)	(0.227)	(0.636)	(0.331)
POR†	2.7368***	1.0102***	2.6444***	1.0130***	<u>0.7682</u>***	0.9399***	-0.1594	0.6628
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.361)	(0.149)
SDO	3.2839***	1.0264***	3.1670***	1.0293***	-0.0805	0.9522*	0.3678**	1.0164***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.996)	(0.090)	(0.031)	(0.000)
SEA†	0.4047***	1.0204***	0.3814***	1.0363***	-1.5946**	<u>0.9096</u>***	0.4594***	<u>0.9452</u>***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.016)	(0.000)	(0.000)	(0.000)
SFO†	0.7640	0.9268***	0.3387***	1.0740***	0.9096	0.9185***	0.1174	703.24?
	(0.202)	(0.000)	(0.002)	(0.000)	(0.268)	(0.000)	(0.888)	(0.856)
STL	5.4627	1.0205***	0.0915	0.9324***	1.6374	1.0264***	0.2245***	1.0670***
	(0.102)	(0.000)	(0.324)	(0.000)	(0.671)	(0.000)	(0.004)	(0.000)
USA†	2.8164***	1.0311****	0.3034***	1.0494***	0.6337***	0.9744***	0.2931**	0.9881***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.018)	(0.000)

Notes: $p-$values are in parenthesis. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level *and* for results which are theoretically feasible: $\theta < 1,\ \beta < 1$. ‡Miami sample begins in 1979. Cities identified with a '†' are cities where estimates in at least one model are statistically significant and with estimates which conform to theory, $\beta, \theta < 1$. Underline coefficients are the minimum and maximum estimates.

Figures

Figure 1: City Output Gap Deviations from US: 1969-2008

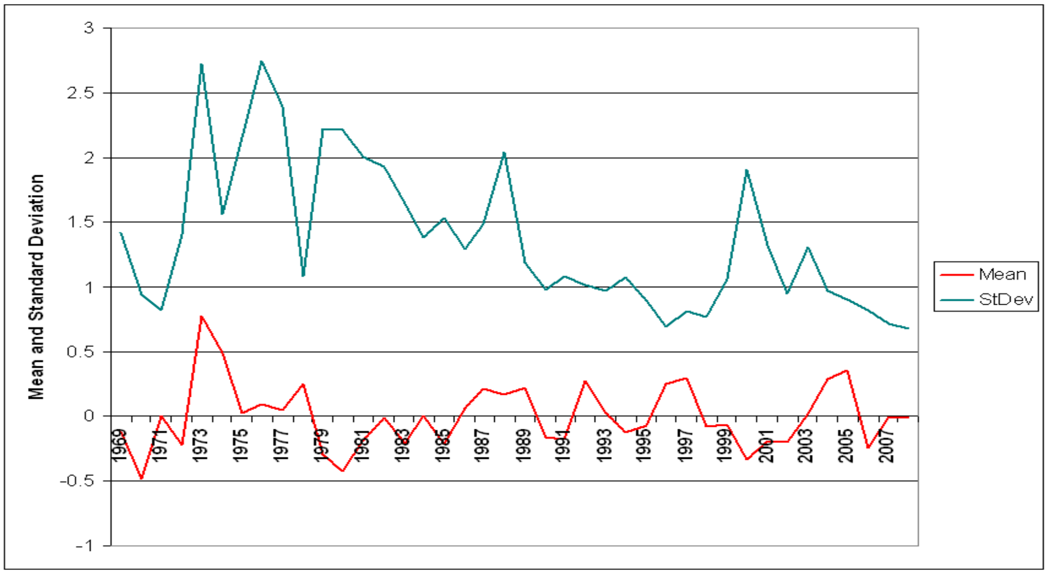

Figure 2: City Marginal Cost Deviations from US: 1969-2008

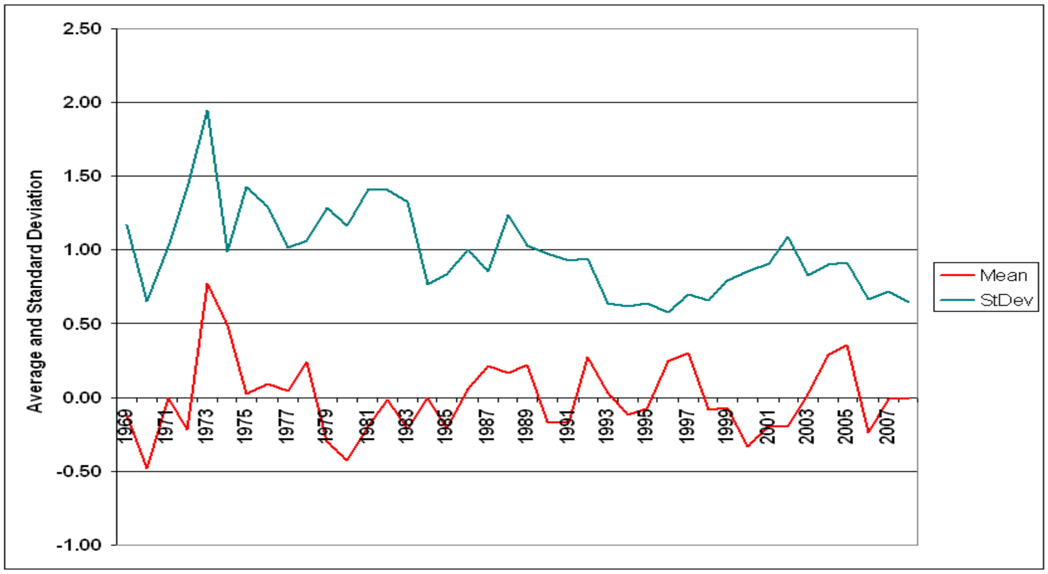

Figure 3: Inflation Deviations from US: 1969-2008

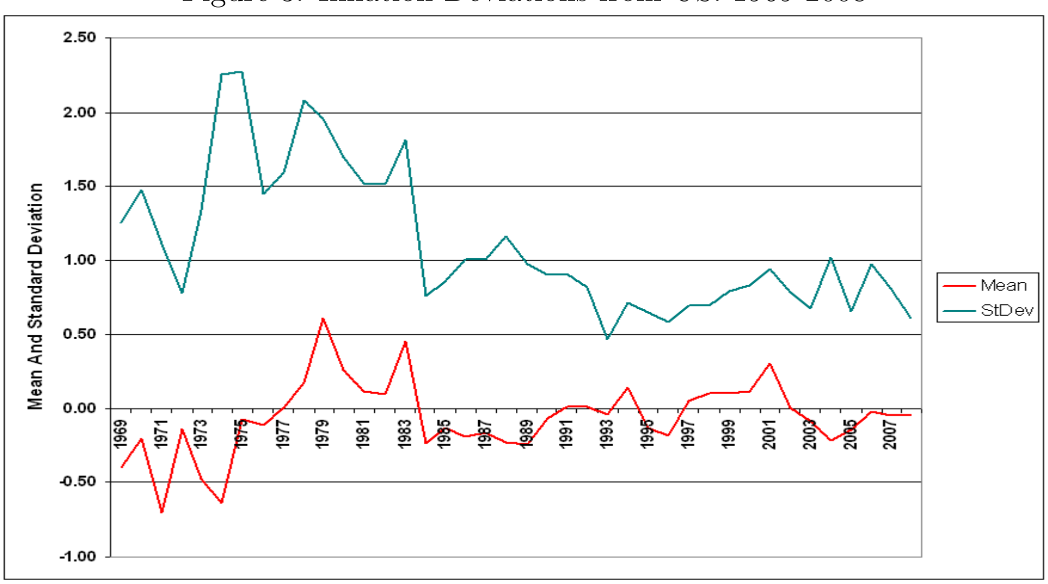

Figure 4: Average and Standard Deviation of Real Wages: 1969-2008