The Linkage Between Prices, Wages,
and Labor Productivity:
A Panel Study of Manufacturing Industries

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ABSTRACT

This paper investigates the long-run relationship between prices and wage-adjusted productivity as well as between real wages and average labor productivity at the industry level for a panel of 459 US manufacturing industries over the period 1956-1996. Our approach highlights a number of problems with panel unit root and panel cointegration procedures and employs methods to overcome these limitations. Panel cointegration test results strongly reject the null of no cointegration in the panel between both prices and wage-adjusted productivity and between labor productivity and real wages. We also demonstrate that many (but not all) individual industries support a cointegrating relationship between these variables. Stability tests by industry support a constant long-run relation, and a stable cointegration equilibrium for most industries across the panel. Granger causality tests show that prices are weakly exogenous and cause movements in unit labor cost. Increases in prices lead to less than one-for-one movements in unit labor costs, although the one-for-one relationship receives some support for a sub-sample of industries. Bi-directional Granger-causality is found between real wages and productivity; however, a one-to-one relationship is strongly rejected between real wages and productivity. Increases in labor productivity are associated with a less than unity increase in real wages.

1. Introduction

Policy-makers and financial analysts cite wage pressures and productivity gains as leading factors in explaining inflation. This cost-push explanation of inflation, however, is questioned by Mehra (1991, 1993, 2000), who shows that prices explain wages, but that wages are not a causal factor in determining inflation. Studies by Hu and Trehan (1995) and Gordon (1988, 1998) report evidence indicating that wage growth has no predictive content for inflation, rejecting the cost-push view. Emery and Chang (1996) and Hess (1999) demonstrate that these finding are sensitive to the sample period examined. Ghali (1999), using Granger-causality tests, finds that wage growth does help to predict inflation, supporting the cost-push view. A related but also relatively unexplored relationship is that between real wages and productivity. Although this link is the building block of many macroeconomic models, and is frequently cited in intermediate macroeconomic textbooks, few empirical works have tested this relationship. [1]

Recently a large number of studies have begun testing long-standing macroeconomic hypotheses using panel unit root and/or panel cointegration tests. However, few studies have employed industry level panel data sets. The current paper contributes to filling this void. It employs manufacturing industry data to evaluate the long-run dynamics between wages, prices, and productivity rather than the traditional approach of examining macroeconomic aggregates. More specifically, using annual 4-digit industry level data from the manufacturing sector over the period 1958-1996, this paper examines the relationship between prices and wage adjusted productivity, as well as the linkage between productivity and real wages, using panel unit root and cointegration estimation methods. The increased power and precision of the panel methods are particularly valuable in this context since they allow the researcher to more accurately test for the existence of a one-for-one cointegrating equilibrium between labor market variables and industry output prices. An additional objective of this paper is to show the advantages and disadvantages of employing panel unit root and cointegration tests. We demonstrate that the considerable heterogeneity of the data imply that the practitioner must be cautious in making inferences about the linkage between variables when using either pooling estimation methods or aggregate level data. Our methodology accommodates for heterogeneity by averaging coefficients, as well as examines outlier effects through quartile analysis. Heterogeneity of the cointegrating vector and cross correlations are accommodated through analysis by industry of the extent of cointegration across the panel and Monte Carlo simulations that calculate correctly sized critical values.

Our results suggest that a stable, long-run relationship exists between prices and wage-adjusted productivity as well as between real wages and productivity for many, but not all industries. Both relationships, however, have considerably varied estimates and in most cases differ from the one-for-one linkage found by Mehra and others in aggregate level data. Furthermore, Granger causality tests support one-way causation from prices to per-unit labor costs (ULC) in both the short and the long-run. Hence, the industry level data reject the standard cost-push explanation of wage pressures contributing to inflation, supporting the aggregate level findings of Mehra (1991, 1993, 2000) and others. Our findings suggest that prices may be driven more by demand side factors rather than supply side factors. Results further support bi-directional Granger-causality in the long run between real wages and labor productivity. This implies that changes in real wages lead to productivity changes, and is not inconsistent with the efficiency wage hypothesis. At the same time productivity movements affect real wages, which is consistent with efficient labor markets.

The paper is organized as follows. Section 2 provides a motivation for our study. Section 3 provides a simple theoretical foundation upon which our empirical results are based. Section 4 discusses the different panel testing methodologies employed. Section 5 discusses the data set employed and presents our empirical results. Section 6 presents a summary and conclusion.

2. Motivation

Business periodicals such as the Wall Street Journal and Business Week regularly report per-unit labor costs and labor productivity growth, and claim that they are leading factors in explaining inflation. In the February 10, 2000 issue of the Wall Street Journal, one can find the statement that "Economists have credited rising productivity-defined as output per hour worked-with allowing the longest economic expansion in U.S. history to continue without the kind of inflationary pressures normally associated with rapid growth." (p. C2). One implication of the expectations augmented Phillips curve is that prices are set as a mark-up over productivity adjusted wages, defined as nominal wage minus labor productivity. At the macro level, Mehra (1991) investigates the causal linkage between the aggregate price level and productivity adjusted wages. He finds that inflation and the growth rate of per-unit labor costs are correlated in the long-run, and that inflation surprisingly Granger-causes growth in per-unit labor costs (ULC). Such findings are inconsistent with the price mark-up hypothesis. Using more modern cointegration and stationarity tests, as well as alternative measures of the price level and different sample periods, Mehra (1993, 2000) examines the robustness of his earlier results, and demonstrates that aggregate ULC and the aggregate price level contain a common stochastic trend. He finds bi-directional Granger-causality between these variables. Most recently, Mehra (2000) demonstrates that (GDP deflator) inflation always helps predicts wage growth and this relationship is stable across all sample periods, but that wage growth predicts inflation only during the period 1966Q1-1993Q4, a period during which inflation steadily accelerated. One objective of this paper is to investigate whether the aggregate level findings of Mehra (2000) hold up at the industry level using panel estimation methods.

A further contribution of this paper is to highlight the advantages of panel cointegration testing in industry level analysis, while overcoming some of the problems associated with panel data testing procedures. Recent panel cointegration procedures yield considerably more precision by pooling the long-run relationships across the panel while allowing the associated short-run dynamics and fixed effects to be heterogeneous across different members of the panel. At the same time, however, panel *unit-root* tests suffer from five potentially severe drawbacks: i) difficulty in interpreting the null hypothesis; ii) the lack of formal stability tests; iii) the possibility of incorrect standard errors occurring when mixing stationary and non-stationary data; iv) possible heterogeneity of the first order autoregressive coefficients; v) contemporaneous correlations that may lead to a spurious rejection of the null. In addition to these limitations, panel *cointegration* tests suffer from the problem of normalization. This problem can potentially bias the cointegration estimation and testing procedures.[2]

A key concern with panel unit root procedures is that the alternative hypothesis states that at least one series is stationary (Im, Pesaran and Shin or IPS 2003) or that all the series are stationary (Levin, Lin, and Chu 2002). McKoskey and Kao (2001) and Pedroni (1995, 1999), for cointegrated series, have equivalent alternative hypotheses for the estimated residuals. In practice, the researcher does not want to conclude cointegration across the panel if it occurs infrequently.[3] To address this issue, Engle and Granger (1987) cointegration tests are conducted on our industry level data in such a way that we can evaluate the frequency of a cointegrating equilibrium by examining the results from different quartiles. Furthermore, parameter stability tests by industry are conducted to determine whether a structural change has occurred in the cointegrating relation. These tests also provide a robust method of testing for cointegration by industry.

In practice, rejection of the null of nonstationary residuals does not imply that most, or even all of the series are cointegrated. In this case, panel cointegration procedures or Granger-causality tests may yield spurious test statistics. To avoid the mixing of I(1) and I(0) series, we conduct our estimation using a sub-sample of our 459 industries that exhibit cointegrating relations using the univariate Engle-Granger test. We also compare the coefficients to results from the full sample to ascertain whether the estimates are robust to sample selection.

As for the fourth potential hazard, several panel cointegration tests are adopted that allow for different restrictions on the cointegrating vectors, autoregressive coefficients, and patterns of serial correlation. Given heterogeneity among industries as well as different null/alternative hypotheses, it would not be surprising to find that different methods yield different findings. Hence, we examine the robustness of different panel unit-root and cointegration tests in the investigation of the linkage between industry output prices and ULC.

Perhaps the most commonly cited problem with panel unit-root or cointegration procedures is that their increased power is derived from pooling or combining N independent regressions. In practice, however, regional and macroeconomic shocks across industries can lead to cross-correlated residuals, contributing to possible false inference in support of stationarity and cointegration. This paper accounts for contemporaneous correlation by running a Monte Carlo simulation to generate the correctly sized t-statistics. Other standard approaches. such as demeaning or the use of seemingly unrelated regressions (SUR), are not appropriate in this context, because we allow heterogeneity in estimated coefficients and our cross section exceeds our time dimension (i.e., $N > T$).

Lastly, we also show that panel cointegration results using Engle-Granger estimates can suffer from normalization problems and following Ng and Perron (1998), the appropriate procedure is to use the more integrated variable as the regressor. When this is unclear, we present both specifications.

In order to address these issues we first investigate the time series properties and linkages between prices and per-unit labor costs (which can be equivalently defined as productivity adjusted wages; henceforth ULC) for a panel of 459 manufacturing industries for the period 1958-1996. Given the heterogeneity of industries, we isolate those industries for which a long-run relationship exists between prices and ULC. We then employ a panel vector error correction model (PVECM) framework to test for Granger-causality between (log) output price and (log) ULC in cases where cointegration is found to exist between the series in question. We also compare the results to the broader sample to determine whether the results are robust across the entire manufacturing sector. Second, we examine the linkage between real wages (nominal wage divided by industry product price) and labor productivity (industry output in real terms divided by number of employees in the industry). For a perfectly competitive industry with a Cobb-Douglas production function, the real wage is proportional to average productivity. This implies that the cointegrating vector between (log) of real wage and (log) labor productivity should not be significantly different from (1,-1).

3. Theoretical Discussion

In this section we provide the theoretical foundation for our subsequent empirical analysis. Assume an industry operates with a Cobb-Douglas production function which is homogeneous of degree z. Consider the production function

$$Q = f(K,L) = AK^{\alpha_1}L^{\alpha_2} \tag{1}$$

where $\alpha_1 + \alpha_2 = z = 1$ under constant returns to scale, Q represents the quantity of output, L represents number of workers, K represents the capital stock, and A represents technological progress which we will normalize to 1.[4] By Euler's theorem, for a production function homogenous of degree z, we have

$$zQ = (\partial Q/\partial K)K + (\partial Q/\partial L)L \tag{2}$$

If we assume perfect competition in the factor markets, then factors of production are paid their marginal product. Define W as the nominal wage, P as the output price, and R is the rental cost of capital. Then the real total factor payment to labor (W/P)L is given as

$$(W/P)L = (\partial Q/\partial L)L = (\alpha_2 AK^{\alpha_1}L^{-\alpha 2})L = \alpha_2 Q \tag{3}$$

and the total real factor payment to capital (R/P)K, is given as

$$(R/P)K = (\partial Q/\partial K)K = (\alpha_1 AK^{-\alpha_1}L^{\alpha 2})K = \alpha_1 Q \tag{4}$$

Substituting (3) and (4) into (2) yields

$$zQ = (R/P)K + (W/P)L = \alpha_1 Q + \alpha_2 Q \tag{5}$$

where α_2 is the labor share of nominal output (WL/PQ), and α_1 is the capital share of nominal output (RK/PQ).

We posit a price mark-up equation where prices are marked-up by a factor, k, over total per-unit costs. This is given by;

$$P = k(WL/Q + RK/Q) \quad (6)$$

Under perfect competition in the product market, total revenue (PQ) is equal to cost of operation (WL + RK) in the long-run. In this case $k = 1$. If total revenue is greater than cost of operations, then $k > 1$ and there will be imperfect competition. If $z > 1$ ($z < 1$), then we have increasing (decreasing) returns to scale. If $z = 1$, then we have constant returns to scale. If $k > 1$ and $z < 1$, then we have imperfect competition and decreasing returns.

Equation (6) can be rewritten as

$$P = k\{WL/Q+(\alpha_1/\alpha_2)WL/Q\} = k[1+(\alpha_1/\alpha_2)]WL/Q = (kz/\alpha_2)(WL/Q) \quad (7)$$

Recall that $z = \alpha_1+\alpha_2$ for a Cobb-Douglas production function. We thus have the product price being proportional to per-unit labor costs. Taking natural logs of (7) and denoting natural logs by lower case letters we can write (7) as

$$p^i = \beta_0 + \beta_1 ulc^i \quad (8)$$

where, $\beta_0 = \ln(kz/\alpha_2)$ and $ulc^i = [w^i - (q^i - l^i)]$, which is often called productivity-adjusted wages (where superscripts denote industry i). This is a cointegrating relation, if both p^i and ulc^i are I(1) series. The parameter β_1 can be interpreted as an elasticity. With respect to the constant term, we can calculate the average value of α_2 for each industry over time. This value should be relatively constant over time if the industry operates under a Cobb-Douglas production function. Equation (8) posits that the output price of industry i depends on unit labor costs.

Given equation (3), and a profit maximizing industry with a chosen level of capital stock and rate of technological progress, we can obtain the familiar marginal productivity condition. In perfectly competitive long-run equilibrium, an industry will maximize profits by employing labor up to the point where the marginal product of labor is equal to the real wage. For the Cobb-Douglas production function this gives the equation

$$(w^i - p^i) = \lambda_1(q^i - l^i) + \ln(\alpha_2) \quad (9)$$

If the time series properties of (w^i-p^i) and (q^i-l^i) are such that they each contain one unit root, and the labor share, α_2, is constant, then the associated cointegrating relation is given in equation (10) as

$$w^i-p^i = \varphi_0 + \varphi_2(y^i - l^i) \quad (10)$$

where, the theoretical value of φ_2 is 1.

Equation (8) depicts a long-run cointegrating relation between ulc and industry output price. Equation (10) depicts a long-run cointegrating relation between real wages and average productivity. These two equations are the primary focus of our study.[5] If two series are cointegrated, Granger-causality exists in at least one direction; however, the direction of the causality must be examined through empirical estimation. In this paper we also investigate Granger-causality between ulc and industry output price, as well as Granger-causality between real wage and average labor productivity.

4. Empirical Methodology: Panel Tests

A. Residual Based Panel Cointegration Tests and Estimation Procedures

A precondition of panel cointegration estimation procedures is that the variables possess unit roots and are cointegrated. This paper adopts the Im, Pesaran and Shin (IPS, 2003) test, which possess substantially more power than single-equation ADF tests. The IPS procedure allows for heterogeneity in ρ and α, and averages the *t*-statistics from *N* independent ADF regressions:

$$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} + \sum_{j=1}^{p} \theta_{ij} \Delta y_{i,t-j} + v_{it}, \quad (11)$$

for $i=1,...,N$ series, $j=1,...,p$ ADF lags and $\rho_1 = ,\ldots, \rho_N = \rho$. The null hypothesis is that $\rho=0$ and the alternative is that at least one series has a value of ρ significantly less than zero. The limiting distribution is given as:

$$\sqrt{N}\,\frac{(\bar{t}_{ADF} - \mu_{ADF})}{\sqrt{(\sigma^2_{ADF})}} \rightarrow N(0,1) \tag{12}$$

where the moments μ_{ADF} and σ^2_{ADF} are from Monte Carlo simulations, and $\bar{t}_{ADF}$ is the average estimated ADF *t*-statistics from the sample. The power to reject the null increases by the $\sqrt{N}$.

McKoskey and Kao (2001) and Kao (1999) developed two straightforward panel cointegration tests that are essentially cointegrating Levin-Lin-Chu (LLC) and IPS tests or panel Engle-Granger procedures.[6] Their power to reject the null increases by the square root of N; thus, both panel cointegration procedures possess substantially more power than single series Engle-Granger tests. The first step in the procedure estimates the following regression:

$$y_{it} = \alpha_i + \beta_i x_{it} + e_{it}, \quad i = 1, \ldots N, \quad t= 1,\ldots,T . \tag{13}$$

The second step tests if the estimated residuals $\hat{e}_{it}$ follow a stationary process:

$$\Delta \hat{e}_{it} = \rho_i \hat{e}_{i,t-1} + \sum_{j=1}^{p} \theta_{ij} \Delta \hat{e}_{i,t-j} + v_{it} \,. \tag{14}$$

The cointegrating LL procedure imposes a common β and ρ across the series. The null hypothesis of no cointegration is given by H_0: $\rho = 0$, and the alternative is that all the series are cointegrated since the coefficients are assumed identical across the panel. The IPS cointegration procedure relaxes the homogeneity assumption and accommodates for heterogeneity in both the cointegrating vector and first-order autoregressive coefficients, allowing both β and ρ to vary by industry. The ADF *t*-statistics are pooled and compared to a panel test statistic that is based on an average *t-statistic* obtained from Monte Carlo simulations assuming independence across industries. The drawback of this procedure, however, is the interpretation of the null and alternative hypotheses. The null hypothesis of no cointegration is given by H_0: $\rho_i = 0$, and the alternative is that "enough of the individual cross-sections have statistics 'far away' from the means predicted by theory were they to be generated under the null" (Kao, 1999; See also Kao and Chiang, 2000). The approach employs (13) and (14), and if the average *t*-statistic is substantially less than the μ_{ADF}, we reject the null that all the series possess a unit root process. One problem is that the average *t-statistic* can be driven by several very stationary estimated residuals (or outliers) with large negative *t*-statistics; hence, rejection of the null must be interpreted with caution. To gain inference concerning the extent of cointegration across industries, it is also important to investigate the number of series that possess ADF t-statistics that are more negative than μ_{ADF} (i.e. the t-statistic under the null of no cointegration). A second major problem with accommodating for heterogeneity in tests for panel cointegration is that there is a strong likelihood that several series in the panel are not cointegrated. If one then applies Kao or Pedroni panel cointegration estimation procedures, the standard errors will be biased because they do not allow for mixing of cointegrated and noncointegrated series.

Pedroni (1995, 1999) developed eight cointegration procedures that impose different restrictions on the cointegrating vector, autoregressive process, and serial correlation of the residual (parametric versus nonparametric). Four of the eight procedures are based on the average *t*-statistic, two methods test the magnitude of ρ, and one adopts a variance ratio approach. Seven of the tests allow the intercept and cointegrating vectors to vary, but the eighth pools both the cointegrating vector and autoregressive coefficient. The main difference between most of the panel procedures is whether the first-order autoregressive coefficients is pooled or averaged. Pedroni's panel test statistics impose a common ρ across industries and tests: H_0: ρ_i =

$0 \; \forall \; i$, versus H_1: $\rho_i = \rho < 0 \; \forall$ i. Pedroni's group t-test averages ρ_i to accommodate for heterogeneity and test H_0: $\rho_i = 0 \; \forall \; i$, versus H_1: $\rho_i < 0 \; \forall$ for at least one i. [7]

B. Panel Cointegration Procedures

In a recent work, Pesaran, Shin and Smith (1999) derive the asymptotics of a pooled mean group (PMG) and mean group (MG) estimator that are panel extensions of the autoregressive distributed lag (ARDL) framework. The PMG procedure constrains the long-run coefficients to be identical (on the assumption that long-run equilibrium relationships are similar across industries), but allows the short-run and adjustment coefficients along with the error variances to differ across industries (since homogeneity for these coefficients and variances is unlikely). This estimator is however biased if heterogeneity occurs because of the imposition of a false homogeneous restriction. The MG estimator accommodates heterogeneity and averages the short and long-run coefficients; if homogeneity occurs, its estimates are inefficient compared to the PMG procedure. Consider the following ARDL model, where x_{it} ($k \; x \; 1$) represents a vector of explanatory variables and u_i represent the fixed effects.[8]

$$y_{it} = \sum_{j=-1}^{p} \lambda_{ij} y_{it-j} + \sum_{j=-1}^{q} \delta'_{ij} \; x_{it-j} + \mu_i + \varepsilon_{it} \qquad (15)$$

To test the homogeneity of the long-run restriction of the PMG estimator across industries, we use Likelihood Ratio tests. Rejection of the null indicates significantly different long-run coefficients across the panel, and implies that the MG estimates must be used. The procedure holds for both stationary and integrated variables, and a Gauss program accompanies their work (www.econ.cam.ac.uk/faculty/pesaran).

C. Parameter Stability Tests

Economists are not only concerned with the magnitude and sign of estimated coefficients, but also whether the estimated parameters are stable over a relevant time period. Moreover, parameter constancy may imply a cointegrating relationship whereas parameter instability and structural change can lead to the finding of no cointegration. Hansen (1992) shows that such tests can provide a robust check for cointegration and provides statistics for parameter stability tests of the cointegrating vector – "since the alternative hypothesis of a random walk in the intercept is identical to no cointegration, the test statistics are tests of the null of cointegration against the alternative of no cointegration." Using a fully modified OLS estimator and a LM procedure, Hansen provides three statistics: Mean-F and Sup-F, are tests of the same null hypothesis but differ in their choice of alternative hypothesis. The Mean-F statistic tests "whether or not the specified model is a good model that captures a stable relationship," and the Sup-F is appropriate for "testing a swift shift in regime." Low LM statistics imply small accumulated estimated residuals, support parameter constancy and provide additional evidence of a long-run stable cointegrating relationship between variables.

D. Normalization

Although it is widely known that residual-based tests for cointegration are asymptotically valid because the least squares estimate is super-consistent, the importance of normalization (which variable is the regressor) has been frequently ignored. Ng and Perron (1997) demonstrate that the OLS, DOLS and FMOLS procedures produce inconsistent and biased coefficients when one of the I(1) variables is a weak random walk and subject to a moving average process. This means that normalization is important when one variable possesses a large stationary component relative to its permanent component. Consider the following example from Ng and Perron:

$$\text{DGP} \qquad x_t = \gamma_1 u_t + e_{1t}\ , \quad e_{1t} \sim N(0,1) \qquad\qquad y_t = \gamma_2 u_t + e_{2t}\ , \quad e_{2t} \sim N(0,1) \tag{16}$$

$$u_t = u_{t-1} + v_t \quad , \quad v_t \sim N(0, \sigma_v^2)$$

Substituting out the common trend in x_t and y_t, we obtain:

$$y_t = \beta_x x_t + e_{2t} - \beta_x e_{1t}\ , \quad \beta_x = \gamma_2/\gamma_1 \quad \text{or} \tag{17a}$$

$$x_t = \beta_y y_t + e_{1t} - \beta_y e_{2t}\ , \quad \beta_y = \gamma_1/\gamma_2 \tag{17b}$$

If $\gamma_1 \rightarrow 0$, the moving average or idiosyncratic component of y_t dominates the stochastic trend or integrated component in x_t. Ng and Perron's proofs and simulations show that the estimate of β_y is consistent but the estimated β_x is not. They argue that the regressor should have the larger permanent component. "As is well known, the greater are the variations in the regressors, the more precise is the parameter estimates." Secondly, "given that $\gamma_1 \rightarrow 0$, $\beta_x \rightarrow \infty$ and $\beta_y \rightarrow 0$, asymptotically, the regression in (17a) with y_t as the regressand has a variance that diverges at the same rate as γ_1 approaches 0." The regression in (17b) with x_t as the regressand is, on the other hand, invariant to γ_1 and has finite variance in the limit. In terms of application, the authors demonstrate that in the Fisher equation, both equation (17a) and (17b) yield coefficients less than one. They show that the traditional specification of interest rates regressed on inflation is incorrect (such as 17a) and should be reversed (e.g., 17b). Inflation should be treated as x_t (the regressand) because it possesses a larger mean-reverting process than interest rates, which has a relatively larger permanent component as a percentage of its variance. Hence, equation (17b) yields consistent estimates while estimates for (17a) will be biased downward.

E. Granger Causality Testing

Consider the bi-variate system (p_i , ulc_i). If p_i and ulc_i contain unit roots, and they are not cointegrated, one could estimate a form of equation (8), in which the first differences of the variables are regressed on each other. Engle and Granger (1987) have demonstrated that if the series are cointegrated, simply first differencing the data will induce a non-invertible MA representation.[9] They derive the Granger representation theorem that any cointegrated system can be written as an error correction model (ECM).

The VECM for two variables y and x is shown below in equations (18a) and (18b),

$$\Delta y_t = \alpha_0 + ec_y (y_t - \alpha_1 - \beta_1 x_t)_{t-1} + \sum_{i=1}^{L} \gamma_{yi} \Delta x_{t-i} + \sum_{i=1}^{L} \psi_{yi} \Delta y_{t-i} \qquad (18a)$$

$$\Delta x_t = \alpha_0 + ec_x (x_t - \alpha_2 - \beta_2 y_t)_{t-1} + \sum_{i=1}^{L} \gamma_{xi} \Delta x_{t-i} + \sum_{i=1}^{L} \psi_{xi} \Delta y_{t-i} \qquad (18b)$$

Let ec_x designate the error correction coefficient in the x-equation and ec_y be the error correction coefficient in the y-equation. If $ec_x = 0$, then x_t is weakly exogenous in the sense of Engle, Hendry and Richard (1983). If $ec_y = 0$, then y_t is said to be weakly exogenous.[10] Weak exogeneity can be tested by estimating the VECM and testing for the significance of the error correction terms in each equation. Since all terms in the VECM are stationary, standard Student t-tests will yield valid inference.

If we let $y = p_i$ and $x = ulc_i$ then the coefficients on the error correction terms for the price and ulc equations are $ec_{\Delta p}$ and $ec_{\Delta ulc}$,respectively. If $ec_{\Delta ulc}$ is insignificantly different from zero, while $\alpha_{\Delta p}$ is significant, then unit labor costs are said to be weakly exogenous. If $\alpha_{\Delta p}$ is insignificantly different from zero, while $ec_{\Delta ulc}$ is significantly different from zero, then industry output price is said to be weakly exogenous. If the lagged values of changes in ulc^i in the price equation are significantly different from zero, and the lagged values of changes in prices in the unit labor cost equation are not different from zero, then unit labor costs Granger-cause output price in the short-run. However, if the lagged changes in prices in the unit labor cost equation are significant as well, then there is bi-directional Granger causality between prices and unit labor costs. If $\alpha_{\Delta p}$ in the price equation is significantly different from zero, then there is long-run Granger causality, in that prices adjust to disequilibrium between prices and unit labor costs.[11] In single equation methods such as those used in panel estimation procedures, the issue of normalization is important. For this reason, we estimate two error correction models: one with $(y_t - \alpha_1 - \beta_1 x_t)_{t-1}$ as the error correction term and another with $(x_t - \alpha_2 - \beta_2 y_t)_{t-1}$ as the error correction term. In this way we are able to determine the effects of different normalizations.

5. Data and Empirical Results

The NBER Manufacturing Productivity Database employed in this paper was developed through a joint effort between the National Bureau of Economic Research (NBER) and the U.S. Census Bureau's Center for Economic Studies (CES). This database contains annual industry-level data on output, employment, payroll, total factor productivity, and various industry-specific price indexes. The database covers all 4-digit manufacturing industries from 1958-1996 for 459 industries using 1987 SIC codes. We express all data in natural logs.

A. Unit Root Tests

Table 1 investigates the integration properties (through the use of ADF tests and IPS panel unit root tests) for the 459 industries for the variables: i) natural log of output price [p=ln(Price)], ii) log wage adjusted productivity or unit labor costs, ulc=[ln(WL/Q)], iii) log of real wages [w=ln(wage)], iv) labor productivity (log of output per worker), y=ln(Q/L), v) log of labor share [ln[WL/PQ)]. To illustrate the heterogeneity of the data we report values for the mean, median, highest, lowest, 25%, and 75% percentiles. IPS panel unit root statistics cannot reject the null of a unit root for prices, ULC, productivity, and real wages as the t-statistics are not significantly below the critical value of μ_{ADF} =-1.51.[12] Hence, our variables appear to contain a unit root process. We then impose the restriction of (1,-1) between prices (p) and wage adjusted productivity (ULC) as well as between real wages (w) and labor productivity (y) and test whether the residual follows a stationary process (see columns 5 and 6 of Table 1, respectively). The test of the restriction (1,-1) on w and y is equivalent to testing the stationarity of α_2 or labor share in equation (9). Using the full sample of 459 industries, the IPS statistics cannot reject a unit root process in the residuals for both specifications, implying that a one-for-one relationship is not supported between prices (p) and ulc, contrary to the results of Mehra (2000), who employ aggregate macro data. IPS panel statistics also cannot reject a unit root process for labor share. The lag length used in conducting unit root tests and the subsequent cointegration tests is 1. In 80% of the cases, the coefficient associated with a 2nd lag was insignificant. This is not surprising give our use of annual data.

B. Panel Cointegration Tests

Table 2 reports Engle-Granger cointegration results for the bivariate vectors (p, ulc), corresponding to equation (8), and (w, y), corresponding to equation (9) or (10). Due to potential normalization concerns, we alternate both the regressand and regressor. Engle-Granger t-statistics for most (but not all) industries cannot reject a nonstationary process. To determine whether these results are due to a lack of power, we report a panel Engle-Granger test based on whether the sample mean is significantly different than an average cointegrating mean μ_{ADF} of –2.026 obtained by Monte Carlo simulation (given by McCoskey and Kao, 2001). This is similar to μ_{ADF} in equation (12) except it is for the estimated residual. The mean value for the EG (row 1 in Table 2) test for normalization (1a), where ulc is the regresand, supports a cointegrating relationship, but the specification in (1b), where p is the regresand, cannot reject the null. Normalizations (2a) and (2b) indicate that regardless of whether we normalize on real wage (w) or on labor productivity (y), we reject the null of no cointegration between real wages and productivity. To determine whether there is a one-to-one linkage between price (p) and productivity adjusted wages (ulc) and between real wage (w) and labor productivity (y), the bottom rows of Table 2 reports the average FMOLS coefficient, its standard error, and the median and 75% and 25% percentile values. For ulc on p, w on y and y on w, we find that the mean FMOLS coefficient, β, is significantly different than one. Quartile analysis further demonstrates that most industries possess coefficients substantially different than one. Changes in price (p) are associated with significantly less than one-for-one movements in wage-adjusted productivity (ulc) (normalization 1a). This is contrary to the one-to-one linkage found by Mehra (2000) using aggregate data. For our industry level data, productivity shocks are associated with substantially less than one-to-one real wage innovations (normalization 2b), and supports the observation by Gordon (2000) that real wage movements have lagged behind increases in productivity. It also suggests that labor share has experienced a permanent decline in manufacturing industries from 1959-1996. Comparing the value of β in normalization (2b) with that in (2a) suggests that there is a normalization problem; as the mean value of 1.29 in case (2a) is not equal to the inverse of .53 (the value of β in normalization 2b). (We investigate the issue of causality below).

The issue of normalization is important for both the price-unit labor cost (p, ulc) relation as well as for the real wage-productivity (w, y) relation. Ng and Perron (1997) identify that the regressor should be the "more integrated" variable. This is the variable that has the largest permanent component. To compare variability, we divide the industry variables by their sample means and then compare their standard deviations. Logged price has a standard deviation more than three times that of ulc, while (log) real wage and (log) productivity have standard deviations that are within 10% of each other. A second means by which we can discern which variable is more integrated is to inspect the size of the ρ coefficient in an ADF regression. The average ρ

for p and ulc are -.01 and. -.08, respectively and suggest that price is slightly more persistence than ulc, and thus p should be the regresand. In terms of (log) real wages and (log) productivity, it is less clear, as ρ is -.12 and -.09, respectively. For real wages and productivity, it is unclear which variable should be the regressor and thus, we need to carefully examine both specifications. Of course, to be precise one would want to determine the size of the permanent component for each of the 459 industries for each of the specifications. Our objective here, however, is to point out the implications of ignoring the issue of normalization in panel cointegration tests, rather than to ascertain what is the appropriate normalization in each industry for each specification.

C. Robustness Tests

As discussed above, there are several potential problems with the above panel test that are intrinsic to most panel testing procedures, including aspects of inference, contemporaneous correlation, serial correlation and the mixing of I(1) and I(0) variables. Since our procedures allow for heterogeneity in the cointegrating vector, the alternative hypothesis, similar to the IPS procedure, can be driven by only a few stationary residual series. To address this concern and determine whether a few or many industries drive the *t*-statistics and influence rejection of the null, we review Table 2. In all four specifications, the median is close to the mean, and in (1a), (2a) and (2b) (see top panel of Table 2) the median is substantially larger in absolute value than the average cointegrating mean ADF t-statistic (μ_{ADF}) of –2.026 generated under the null (given by McKoskey and Kao, 2001). For the specification w on p (p on w), tests indicate that 400 (223) industries have more negative t-statistics on the first-order autoregressive coefficient than the value of μ_{ADF}. In addition, 359 (144) industries have t-statistics that are .3 more negative than the mean ADF t-statistic, where .3 represents a considerable distance from the average mean.

For the second specification, y on w (w on y), the Engle-Granger cointegration results show that 320 (277) industries have t-statistics more negative than μ_{ADF} and 295 (260) industries having t-statistics with values .3 more negative than the critical value. Hence, a long-run relationship has widespread support using specification (1a) and (2a). The other normalizations reveal less industry support for a cointegrating relationship.

We next conduct tests for whether the long-run relationships have stable parameter estimates. At the 95% level, the Hansen (1992) test of the null of stable parameter, reject the specification w on p (p on w) for 15 (243) industries using the Mean-F statistic and 3 (12) industries using the Sup-F statistic. Tests reject the specification w on y (y on w) for 120 (108) industries using the Mean-F statistic and 0 (0) industries for the Sup-F statistic. Hence, most industries exhibit stable long-run parameters. Our finding of stability is interesting given that Emery and Chang (1996), Hess (1999) and Mehra (2000) find an unstable relationship between aggregate wage and price data. Our Mean-F results are consistent with this finding when ulc is the regressor, as approximately half the industries reject stability; however, we argue that this specification is not appropriate due to the normalization issues discussed above.

Another concern with panel statistics is contemporaneous correlation of the estimated residuals. Following O'Connell (1998), we examine the correlation matrix to determine the extent of contemporaneous correlations. O'Connell found that correlations higher than .3 produce significant size distortions. The average correlation, across the 459 industries for the specification ulc on p is only .02 and for the productivity (y) on real wage (w) specification has a value of .07. Monte Carlo simulation based on these statistics reveal a nominal size distortion of 8% and 19% respectively, instead of the conventional 5%. To eliminate this problem we use size adjusted critical values, which decreases the 5% critical values from a one-sided finite sample t-distribution with value – 1.72 to -2.12 and -2.32, for the .02 and .07 correlations, respectively. The 1% critical values change from -2.40 to -2.85 and –3.20, respectively. This however, does not affect our inferences. Applying (12) to convert the test statistics to a one-sided Normal test, we obtain the test-statistics, –22.7, .96, -16.6 and –18.7.[13] Hence, we reject no cointegration for three of the four specifications (1a, 2a, and 2b). The presence of low average correlations also implies that time-specific means are unnecessary to remove the aggregate (or average) correlations.

One problem, however, with assuming average correlations is that inspection of the correlation matrix reveals the correlations are not identical, possessing high positive and negative correlations, which tend to sum to near zero. In our data, the correlations vary by a large amount, and suggest that the shocks are driven by sector specific factors rather than by identical macroeconomic shocks. The correlations range from a high of .92 to a low of -.88 with 25% and 75% quartile values of -.17 and .27, respectively, for price on ulc. The presence of strong but varied shocks generating the data further suggests the importance of accounting for heterogeneity. Pooling techniques may lead to biased estimates and simply aggregating industry data may lead to loss of information due to averaging out. To estimate the effects of this type of contemporaneous correlation on our critical values, we run 5000 Monte Carlo simulations using the historical correlation matrix of the residuals from the ADF regressions.[14] Our results show that the size distortion substantially increases, as do the size adjusted critical values. The 5% (1%) critical values increase substantially to –7.15 (–9.8); however, we still reject the null of no cointegration at the 1% level for all three cases, given the test-statistics of –22.7, -16.6, and –18.7 for normalizations 1a, 2a, and 2b stated above.

Although the panel statistics, for the most part, support cointegration, inspection of Table 2 reveals substantial differences in ranges between the 25%-75% quartiles, which imply that some, but not all the series are stationary. This indicates one cannot use the entire panel to determine causation or estimate short and long-run relationships because of the presence of both stationary and nonstationary relationships in the full panel of industries. The potential mixing of I(1) and I(0) series will lead to biased standard errors and spurious inference in Granger-causality tests as well as in other panel cointegration methods that assume stationary residuals. To avoid this problem, we estimate a subset of industries that possess stationary residuals using the Engle-Granger 10% critical values. Using these industries, we report Granger-causality results in Table 3 for this sub-sample. To avoid a potential self-selection problem, we also report the full sample results in Table 4 and compare the coefficient estimates (which are unbiased) to those in Table 3 for the sub-samples.

D. Granger-Causality Tests

Table 3 reports short and long-run single equation Granger-Causality test results for different normalizations of the sub-samples. These results are average values of coefficients obtained from single equation Granger-causality tests done on each industry separately. Short-run causality is tested by the joint significance of the lagged dependent variables (here only one). Long-run causality is tested by the significance of the error-correction terms that indicate the speed of adjustment back to equilibrium. Note that in Table 3 we report two different error correction models, one for each normalization. Due to the lack of support for the (1,-1) specification, we do not impose this restriction. The test results strongly indicate one way short-run and long-run causation from prices (p) to unit labor costs (ulc)—see columns 2a and 2b of Table 3--supporting the conclusion of Mehra (1993, 2000). Regardless of whether the error correction term is normalized as in (2a) or as in (2b), both error-correction terms ρ_1 and ρ_2 (for the sub-sample) have the correct sign and are significant, while those for normalizations (1a) and (1b) are insignificant. These two results imply that prices are weakly exogenous. In addition, regardless of the normalization, both β_3 and β_4 for normalizations (2a) and (2b), are significant, while they are insignificant for (1a) and (1b). These results imply short-run causality from prices (p) to wage-adjusted productivity (ulc). Turning to the linkage between real wages and productivity, we find that the error correction terms are significant regardless of the normalization (see ρ_1 and ρ_2 for (3a), (3b), and (4a), (4b). However, for normalization (3b) and (4a) the coefficients are of the wrong sign. Normalization (3a) and (4b) have correct signed error correction terms and they are significant. There appears to be tentative support for long-run bi-directional Granger-causality between real wages and productivity, however, one must be cautious of the normalization. The coefficients on the lagged difference terms (β_3 and β_4) are significant in normalizations (4a) and (4b). In terms of the real wage/productivity relationship, normalization appears to be very important. When productivity is the left hand side variable in the regression (3a), tests show that the error correction term has the correct sign and is significant. The tests reject the null hypothesis that wages do not cause productivity. However, when the normalization is reversed (so that wage-adjusted productivity is the left hand side variable, normalization 3b) we obtain an error-correction term with an incorrect sign. A similar result occurs when testing Granger-causality from productivity to wages (see normalizations 4a and 4b). The ambiguity concerning which is the correct normalization indicates that the practitioner must be careful in stating direction and existence of causality.

To determine whether causation results are robust across the full sample, Table 4 reports quartile estimates for both the long-run coefficients and the error correction terms for the full sample. The size of the error correction term for the 25%, median and 75% quartiles are relatively large and negative for the specification p to ulc (normalization 2b, Table 4). Since the coefficient estimates are unbiased, this provides evidence that the causation finding of price to wage-adjusted productivity is robust across the larger sample. In terms of real wages and productivity, results again depend critically on the normalization, and meaningful inference is not straightforward. These results are reported in order to illustrate the heterogeneity for both short-run and long-run coefficients in Granger-causality tests as well as for the β values. This implies that one cannot pool long-run coefficients in panels that have a large degree of heterogeneity. The differences in the error correction terms further demonstrate the presence of both cointegrated and noncointegrated relationships among the industries.

Responding to a suggestion of a referee, we next investigate the possible correlation between industry structure (measured by degree of concentration) and our finding that price is weakly exogenous and that price Granger-causes productivity adjusted wages. We focus our attention on specification (1b) and (2b) of Table 3. We split the sub-sample of 125 industries into three categories based on the Justice Department's categorization of the Herfindahl-Hirschman index (HHI). The HHI is a commonly accepted measure of market concentration. The HHI takes into account the relative size and distribution of the firms in a market and approaches zero when a market or industry consists of a large number of firms of similar size. The HHI increases when either the number of firms in the market decreases and/or the disparity in size between those firms increases. Values of the HHI less than 1000 indicate low levels of concentration, values between 1000 and 1800 indicate moderate concentration, and values above 1800 indicate a highly concentrated industry or market. Using HHI ratios from the 1992 census of manufacturers report, we segment the 125 industries of our sub-sample (see Table 3) into low, medium and high concentration. This categorization indicates that 80% of our sub-sample of 125 firms and 74% of the full sample of 459 industries have low levels of concentration. We repeat the estimation methods used in Table 3 for specifications (1b) and (2b). The results, reported in Table 5, show that our results are not sensitive to the degree of concentration in the industry. We find that for all levels of concentration, we reject the null hypothesis that price does not Granger cause productivity adjusted wages. We find that productivity-adjusted wages do not Granger cause prices. Our finding, that prices are weakly exogenous and that price Granger causes productivity adjusted wages are not influenced by the degree of concentration in an industry.

E. Panel ARDL Estimates

Table 6 presents short-run, long-run, and speed of adjustment estimates for panel ARDL tests for the relationship between prices and ulc as well as between real wages and productivity. The long-run coefficients average the estimates across industries and are robust to heterogeneity concerns. The coefficients correspond to β_1 and β_2 in Table 3, the short-run coefficients correspond to β_3 and β_4 and the error-correction coefficients (speed of adjustment) correspond to ρ_1 and ρ_2. For the sub-sample of ulc on price (normalization 2b in Table 3), the long run mean coefficient of .89 is not insignificantly different from one. This value is consistent with the average of the coefficients for the first stage of the Engle-Granger (β_2=.87 in Table 3) for the sub-sample and very similar to the mean of individual FMOLS estimates, 0.88 (not reported in the tables). Hence, the data imply that a one-for-one relationship, consistent with economic theory, between prices and wage-adjusted productivity is supported for a sub-sample of industries that are cointegrated. However, across all industries, the long-run coefficient falls to .69 (see row 1, column 2, Table 6) and suggests a less than one-for-one relationship.

For the cointegrated sub-sample, the R^2 of .38 implies that price innovations explain a not insignificant portion of ULC movements. The error correction term is relatively low, indicating a lengthy speed of adjustment. The short-run coefficient is also significant and supports short-run Granger-causality from prices to ulc. The tests reject at the 1% level homogenous long-run coefficients across the sub-sample since the log-likelihood ratio test for homogeneity is 440. Furthermore, the adjusted R^2 falls substantially when the long-run coefficient is restricted across the sample indicating a loss of information when pooling.[15] Log-likelihood tests for the full sample also reject imposing homogenous long-run coefficients and the R^2 also falls when a homogenous long-run coefficient in the full sample. Both statistics however should be viewed with caution due to the mixing of I(0) and I(1) regression, and the potential for incorrect inference (as mentioned above).

The long run ARDL coefficients between real wage and productivity, for both the sub-sample and the full sample, are substantially different than one, and the magnitudes depend on the normalization since the coefficients are not symmetric around one. We find that increases in productivity lead to significantly less than one-for-one increases in real wages and the magnitudes are robust across the sub-samples. The error correction term and short-run coefficients are significant for both specifications regardless of normalization and suggests both short-run and long-run bi-directional Granger-causality exists. The relatively high adjusted-R^2 for these specifications also implies that real wages explain productivity movements well and productivity also explains real wage shocks. Likelihood ratio tests strongly reject homogenous coefficients across the sub-sample and full-sample, and reveal the importance of accounting for heterogeneity in the coefficients. The χ^2 statistics for heteroscedasticity and serial correlation are very low for almost all industries, indicating that we cannot reject the null of no heteroscedasticity and serial correlation in the residuals for most industries for all four specifications.

F. Other Panel Cointegration Test Procedures

We next examine the robustness of the panel test results to different specifications of serial correlation and homogeneity/heterogeneity of the cointegrating vector and first-order autoregressive coefficients by employing alternative cointegration testing procedures. Various panel test results reported in Table 7 reveal strong support for cointegration, as most methods strongly reject the null of no cointegration at the 1% level. One problem with these panel results is their interpretation. The imposition of homogenous long-run coefficients and first-order autoregressive coefficients appears inappropriate given the quartile results reported in Table 4. In addition, while Pedroni's group statistics allow heterogeneity of both β_i and ρ_i, the null and alternative hypotheses lack meaningful inference, since H_0: $\rho_i = 0$ for all *i*, versus the alternative hypothesis H_1: $\rho_i < 0$ for all *i* (Pedroni, 1999). Given the strong possibility of both cointegrated and noncointegrated series, it is unlikely that all or none of the industries satisfy the null or alternative hypothesis. Hence, while our data reject the null of no cointegration, it is not clear what conclusions the practitioner can draw given the high degree of heterogeneity of the first-order autoregressive coefficients.

To increase confidence concerning the number of industries that are cointegrated, we estimate the number of series that are a substantial distance away from the simulated mean of a unit root under the null. Results for the nonparametric t-statistics, allowing for heterogeneous β and autoregressive coefficients, indicate that for the regression ulc on p (p on ulc), 304 (214) industries have t-statistics less than –2.453[16]; for productivity on real wages (real wages on productivity) 358 (193) industries have t-statistics that are substantially less than –2.453. Results for the parametric t-statistic, allowing for heterogeneous β and autoregressive coefficient, are similar.[17] Statistics based on ρ, reveal that most series have autoregressive coefficients different than zero, since for ulc on p (p on ulc), 435 (415) industries possess relatively large negative values of ρ with a mean of -.31 (-.19); similarly, for productivity on real wages (real wages and productivity), 422 (411) industries possess relatively large negative estimates of ρ with a mean of -.38 (-.31). Accordingly, for most industries, test results support a long-run relationship between prices and wage-adjusted productivity as well as between real wages and labor productivity. Panel cointegration tests also strongly reject the null of no cointegration.

An additional problem with these statistics is that they do not correct for contemporaneous correlations in the residuals. Due to more complicated calculations of the variance and distributional assumptions, Monte Carlo simulations to obtain adjusted t-statistics were not computed. Most likely, however, since most of the panel statistics strongly reject at the 1% level and most industries support cointegration (see paragraph above), we suspect that it is unlikely that contemporaneous correlations would change the previous inferences.

6. Summary and Conclusion

This paper investigates the long-run relationship between (log) prices and (log) wage-adjusted productivity as well as between (log) real wages and (log) average labor productivity at the industry level. The panel data set employed consists of annual data on 459 manufacturing industries over the period 1956-1996. The application of panel procedures applied to industry level data offers an alternative approach to estimating the price-wage-productivity nexus, commonly examined using aggregate macroeconomic data.

We highlight both the advantages and the problems associated with panel unit root and panel cointegration procedures and employ methods to overcome these problems. In particular, panel unit root tests suffer from five major problems; i) difficulty in interpreting the null/alternative hypothesis, ii) the lack of formal stability tests, iii) the problem of incorrect standard errors that occur when mixing stationary and non-stationary data; we deal with this by looking, iv) possible heterogeneity of the first-order autoregressive coefficients, and v) contemporaneous correlations that may lead to a spurious rejection of the null. In addition to the above five problems, panel cointegration methods suffer from a sixth problem; vi) the problem of normalization which can potentially bias the cointegration estimates and testing procedures.

We find that industry level data reveal heterogeneous coefficient estimates suggesting that homogenous methods to test for cointegration and to estimate the long-run relationship are likely to yield misleading conclusions. Furthermore, due to differing degrees of correlation across the sample, the standard method of using time specific means to deal with heterogeneity, suggested by Im, Pesaran and Shin, Kao, Pedroni, and others, are not appropriate. To resolve the size distortion problem that arise when there is contemporaneous correlations, we adjust the t-statistics through the use of Monte Carlo simulations. Panel cointegration test results strongly reject the null of no cointegration in the panel between both prices and wage-adjusted productivity and between labor productivity and real wages. Panel cointegration test procedure conclusions further are robust to different restrictions on the long-run cointegrating vector, first order autoregressive coefficient and the error structure. To gain inference concerning the extent of cointegration across the sample, we also demonstrate that many (but not all) individual industries support a cointegrating relationship between these variables. Stability tests, by industry, support a constant long-run relation, and a stable cointegration equilibrium for most industries across the panel.

To avoid the problem of mixing cointegrated and noncointegrated series, we employ Granger-causality tests for a sub-sample of our data that is cointegrated. In an effort to determine whether the results are robust across the full 459 industries we examine the coefficient magnitudes and compare them to the sub-sample as well as use quartile analysis. Granger causality results reveal that prices are weakly exogenous and cause movements in productivity adjusted wages. Bi-directional Granger-causality is found between real wages and productivity. Increases in prices lead to less than one-for-one movements in unit labor costs, although the one-for-one relationship receives some support for a sub-sample of industries. Normalization is also shown to be important and using wage adjusted productivity as the regressor can lead to spurious conclusions. Further, a one-to-one relationship is strongly rejected between real wages and productivity. Increases in labor productivity are associated with a less than unity increase in real wages; hence, we find that labor share for many manufacturing industries from 1958-1996 experienced a permanent decline.

Our findings show that the use of aggregate macro data tends to over simplify the rich heterogeneous nature of the data, and that the convenient Cobb-Douglas production function has problems in fitting important or fundamental macro-economic relationships such as those found between price and wage-adjusted productivity and between real wages and labor productivity. The panel approach can capture or highlight some important problems in macroeconomic theory that deserve further attention and additional research.

Table 1 Unit Root Tests

459 4-digit SIC manufacturing industries 1958-1996

	p	ulc	w	y	p-ulc	α_2
Mean ADF	-.50	-1.14	-1.63	-1.41	-1.43	-1.57
IPS panel t-stat	-.48	-1.09	-1.53	-1.38	-1.38	-1.51
Median ADF	-.54	-1.16	-1.71	-1.43	-1.46	-1.54
Highest ADF	2.29	3.69	2.02	5.09	2.83	2.09
75% ADF	-.26	-.68	-1.04	-.85	-.60	-.89
25% ADF	-.78	-1.65	-2.34	-2.08	-3.76	-2.28
Lowest ADF	-1.88	-4.84	-4.32	-5.78	-4.54	-5.00

p = ln(price), ulc=ln(unit labor costs) or (log) wage adjusted productivity, y=ln(output/number of employees); i.e. labor productivity, w=ln(real wage), and α_2= w-y. . ** indicates significant at 1% level (see footnote 11). IPS panel reported statistics are the averaged demeaned t-statistic.

Table 2 Cointegration Tests for 459 Industries

(1a)	$ulc_t = \alpha + \beta p_t + \varepsilon_t$	$\Delta\varepsilon_t = \rho\varepsilon_{t-1} + \gamma\Delta\varepsilon_{t-1} + \omega_t$
(1b)	$p_t = \alpha + \beta ulc + \varepsilon_t$	$\Delta\varepsilon_t = \rho\varepsilon_{t-1} + \gamma\Delta\varepsilon_{t-1} + \omega_t$
(2a)	$y_t = \alpha + \beta w_t + \varepsilon_t$	$\Delta\varepsilon_t = \rho\varepsilon_{t-1} + \gamma\Delta\varepsilon_{t-1} + \omega_t$
(2b)	$w_t = \alpha + \beta y_t + \varepsilon_t$	$\Delta\varepsilon_t = \rho\varepsilon_{t-1} + \gamma\Delta\varepsilon_{t-1} + \omega_t$

LOG		(1a)	(1b)	(2a)	(2b)
Mean EG	ρ_t	-2.89**	-1.98	-2.66**	-2.74**
Median EG	ρ_t	-2.89**	-2.02	-2.67**	-2.68**
Highest EG	ρ_t	1.31	2.64**	-1.24	-.26
75% EG	ρ_t	-2.43**	-1.89	-2.10	-1.89
25% EG	ρ_t	-3.58**	-2.74**	-3.32**	-3.28**
Lowest EG	ρ_t	-6.89**	-6.55**	-8.62**	-8.32**
Firms 10%	EG	125	82	165	108
β: Mean		.77	1.19	1.29	.53
Median		.79	1.20	1.30	.53
High		5.00	3.28	3.96	2.98
75%		.79	1.35	1.62	.69
25%		-.42	1.06	1.02	.35
Low		-1.51	-.41	-2.59	-.68
FMOLS β: Mean		.72**	.87	1.48*	.44**
Median		.77*	.94	1.55**	.36**
75%		1.06	1.24	1.90**	.57**
25%		.44**	.61*	1.21	.23**
Standard error		.08	.17	.16	.05

The term EG ρ_t, represents the t-statistics associated with the single-equation Engle-Granger test for the first-order autoregressive coefficient. The extent of heterogeneity is shown by reporting the lowest, 25%, Median, 75% and highest EG t-statistics. Industry, 10% EG are the number of industries for which we reject nonstationary residuals at the 10% level using the Engle-Granger test statistics.
**indicates significant at 1% level using Kao's panel Engle-Granger test. ** (*)

indicate that the FMOLS β is significantly different than 1 at the 1% (5%) level.

Table 3 Granger Causality Results

(1a)	$p_t = \alpha_1 + \beta_1 ulc_t + e_{1t}$	$\Delta p_t = \alpha_3 + \beta_3 \Delta ulc_{t-1} + \rho_1 e_{1t-1} + \beta_5 \Delta p_{t-1} + \omega_{1t}$
(1b)	$ulc_t = \alpha_1 + \beta_2 p_t + e_{2t}$	$\Delta p_t = \alpha_4 + \beta_4 \Delta ulc_{t-1} + \rho_2 e_{2t-1} + \beta_6 \Delta p_{t-1} + \omega_{2t}$
(2a)	$p_t = \alpha_1 + \beta_1 ulc_t + e_{1t}$	$\Delta ulc_t = \alpha_3 + \beta_3 \Delta p_{t-1} + \rho_1 e_{1t-1} + \beta_6 \Delta ulc_{t-1} + \omega_{1t}$
(2b)	$ulc_t = \alpha_1 + \beta_2 p_t + e_{2t}$	$\Delta ulc_t = \alpha_4 + \beta_4 \Delta p_{-1} + \rho_2 e_{2t-1} + \beta_5 \Delta ulc_{t-1} + \omega_{2t}$
(3a)	$y_t = \alpha_1 + \beta_1 w_t + e_{1t}$	$\Delta y_t = \alpha_3 + \beta_3 \Delta w_{t-1} + \rho_1 e_{1t-1} + \beta_5 \Delta y_{t-1} + \omega_{1t}$
(3b)	$w_t = \alpha_1 + \beta_2 y_t + e_{2t}$	$\Delta y_t = \alpha_4 + \beta_4 \Delta w_{t-1} + \rho_2 e_{2t-1} + \beta_6 \Delta y_{t-1} + \omega_{2t}$
(4a)	$y_t = \alpha_1 + \beta_1 w_t + e_{1t}$	$\Delta w_t = \alpha_3 + \beta_3 \Delta y_{t-1} + \rho_1 e_{1t-1} + \beta_6 \Delta w_{t-1} + \omega_{1t}$
(4b)	$w_t = \alpha_1 + \beta_2 y_t + e_{2t}$	$\Delta w_t = \alpha_4 + \beta_4 \Delta y_{t-1} + \rho_2 e_{2t-1} + \beta_5 \Delta w_{t-1} + \omega_{2t}$

Specification	ulc $\nrightarrow$ p (1a)	(1b)	p $\nrightarrow$ ulc (2a)	(2b)	w $\nrightarrow$ y (3a)	(3b)	y $\nrightarrow$ w (4a)	(4b)
Sub-sample								
ρ_1 ρ_2	-.07	.05	-.57**	-.48**	-.39**	.50**	.10*	-.33**
β_3 β_4	-.01	-.01	.24**	.27**	.04	.02	-.05*	-.08**
β_1 β_2	1.03	.87	1.03	.87	1.02	.88	1.02	.88
Number of Industries	82	125	82	125	165	108	165	108
Full Sample								
ρ_1 ρ_2	-.05	.03	.15	-.27	-.26	.21	.04	-.15
β_5 β_6	.02	.01	.18*	.23**	.00	.04	-.01	-0.02
β_1 β_2	1.19	.77	1.19	.77	1.29	.75	1.29	.75

**1% * 5% significance using a χ^2 test to test individually the restrictions $\rho_1 = 0$; $\rho_2 = 0$; $\beta_3 = 0$; $\beta_4 = 0$;. No χ^2 test for the ρ–test are reported for the full sample due to the likely presence of nonstationarity. χ^2 tests are conducted for the individual restrictions $\beta_3 = 0$; β_4,=0, since these variables are differenced stationary. The expression → indicates the null\ "does not Granger-cause".

Table 4 Granger Causality Quartile Statistics for Long-Run for 459 Industries

		ulc ↛ p		p ↛ ulc		w ↛ y		y ↛ w	
		(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Median	ρ_1 ρ_2	-.03	.05	.10	-.24	-.22	.14	-.03	-.12
	T stat	-.87	.94	1.10	-1.93	-1.72	.88	.45	-1.22
	β_1 β_2	.79	.90			3.90	2.98		
Highest	ρ_1 ρ_2	.20	.56	2.52	.17	1.14	2.08	1.00	.27
	T stat	3.47	7.71	6.13	.28	4.62	5.25	4.51	1.72
	β_1 β_2	5.00	3.40			1.62	.69		
75%	ρ_1 ρ_2	.00	.11	.28	-.10	-.10	.37	.11	-.05
	T stat	-.16	2.47	2.24	-.97	-.91	1.75	1.22	-1.83
	β_1 β_2	1.04	1.14			1.30	.54		
25%	ρ_1 ρ_2	-.09	-.03	-.03	-.38	-.22	.00	-.04	-.22
	T stat	-1.80	-5.83	-.29	-2.67	-1.72	-.03	-.45	-.54
	β_1 β_2	.42	.61			.35	1.02		
Lowest	ρ_1 ρ_2	-.48	-.80	-.81	-1.11	-4.1	-1.05	-.49	-.96
	stat	-6.21	-5.83	-3.32	-6.02	-2.54	-4.30	-4.64	1.72
	β_1 β_2	-1.51	-2.00			-2.57	-.68		

Significance levels are not given since the t-statistics are invalid given the mixing of I(1) and I(0) series. The expression ↛ indicates the null "does not Granger-cause". No estimates for the coefficients β_1 , β_2 are reported because the normalizations 2a and 2b or 4a and 4b since normalizations
1a and 1b (3a and 3b) are the same as 2a and 2b (4a and 4b).

Table 5 Panel Granger Causality Results
Ranked According to the Herfindahl-Hirschman Index

(1b) $ulc_t = \alpha_1 + \beta_2 p_t + e_{2t}$ $\quad \Delta p_t = \alpha_4 + \beta_4 \Delta ulc_{t-1} + \rho_2 e_{2t-1} + \beta_6 \Delta p_{t-1} + \omega_{2t}$

(2b) $ulc_t = \alpha_1 + \beta_2 p_t + e_{2t}$ $\quad \Delta ulc_t = \alpha_4 + \beta_4 \Delta p_{-1} + \rho_2 e_{2t-1} + \beta_5 \Delta ulc_{t-1} + \omega_{2t}$

	ulc $\nrightarrow$ p			p $\nrightarrow$ ulc		
Sub-sample 125 industries	LOW	MED	HIGH	LOW	MED	HIGH
ρ_2	-.06	-.01	-.03	-.52**	-.48**	-.47**
β_4	-.01	-.02	.03	.25	-.08	.45
β_2	1.03	1.12	.58	1.03	1.12	.58

**1% * 5% significance using a χ^2 test to test the individual restrictions $\rho_2 = 0$; $\beta_4 = 0$. χ^2 tests are conducted for β_4=0, since these variables are differenced stationary.

Herfindahl-Hirschman Index -

Low is below 1000, 80% of 125 industries (74% of 459)
Medium 1000-1800, 11% of 125 industries (14% of 459)
High above 1800, 10% of 125 industries (12% of 459)

Table 6 Panel ARDL Procedure

$$y_{it} = \sum_{j=-1}^{p} \lambda_{ij} y_{it-j} + \sum_{j=-1}^{q} \delta'_{ij} x_{it-j} + \mu_i + \varepsilon_{it}$$

	(1) Sub-sample		(1) Sample		(2) Sub-sample		(2) Sample	
	ulc on p	p on ulc	ulc on p	p on ulc	w on y	y on w	w on y	y on w
LR coeff	.89**	.85**	.69**	.88**[a]	0.48**	1.33**	.46**	1.57**
(s.e.)	.16	.05	.17	.23	0.10	0.05	.07	0.22
EC coefficient	-.11**	-.57**	-.27**	-.07**	-0.32**	-.56**	-.30**	-.33**
(s.e.)	-.012	-.02	.01	.01	0.01	-.02	.01	.02
SR coeff	.113**	.49**	.19**	.06**	.19**	.74**	.14**	.47**
(s.e.)	.012	.03	.01	.01	0.01	.03	.01	.03
R^2	.38	.31	.17	.34	.34	.39	.41	.42
Log-Likelihood	440**	1177**	1673**	1793**	771**	1039**	1229**	1453**
χ^2 (SC) χ^2 (He)	1 0	6 0	17 4	15 7	2 0	2 0	4, 31	10, 18
PMG LR β R^2	.96 .32	.96 .15	.68 .13	1.03 .28	.49 .31	1.37 .35	.64 .36	1.41 .37

Sub-sample uses cointegrating relationships that are assumed stationary using w on p, N= 125 for (1) and w on y for (2), N = 165. [a]five large outliers removed. LR, EC and SR designate long-run, error correction terms and short-run coefficient for the mean group procedure which averages coefficients across the sample. The long run coefficients correspond to β_1 and β_2 in Table III, the short run coefficients to β_3 and β_4 and the EC term (speed of adjustment) to ρ_1 and ρ_2.The last row uses the PMG procedure (pool mean group) that imposes a common long run coefficient; LR , β, and R^2 are the long run coefficient and accompanying adjusted R^2 for this procedure. The next to last row reports the number of industries that reject no serial correction (SC) and no heteroscedasticity (HC) using χ^2 test statistics. Thus, serial correlation and heteroscedasticity does not pose a problem.

Table 7 Panel Test Statistics for 459 Industries

Panel Tests		$p_{it} = \beta_i + \beta_{Ei}ulc_{it} + \omega_{it}$	$ulc_{it} = \beta_i + \beta_{pi}p_{it} + \varepsilon_{it}$
(1) Kao	$\beta_i=\beta$, $\rho_i=\rho$	-57.20**	-59.24**
(2) Pedroni	$\beta_I=\beta$, $\rho_i=\rho$	-254.76	-254.92**
(3) panel v statistics	β_i, $\rho_I=\rho$	167.54**	151.15**
(4) panel ρ statistics	β_i, $\rho_I=\rho$	137.80**	-202.88**
(5) Nonparametric panel t stats	β_i, $\rho_i=\rho$	-39.51**	-50.10**
(6) Parametric panel t stats	β_i, $\rho_i=\rho$	-423.24**	-551.50**
(7) group ρ statistics	β_i, ρ_i	-181.71**	-242.12**
(8) Nonparam. Group t stats	β_i, ρ_i	-42.98*	-53.73**
(9) Parametric group t stats	β_i, ρ_i	-52.57**	-54.03**

Panel Tests	$y_{it} = \beta_i + \beta_{Ei}w_{it} + \omega_{it}$	$w_{it} = \beta_i + \beta_{pi}y_{it} + \varepsilon_{it}$
(1) Kao Homogenous β, ρ	-24.60**	-14.01
(2) Pedroni Homogenous β, ρ	-136.39**	-103.61*
(3) panel v statistics	343.71**	107.11
(4) panel ρ statistics	-254.99**	-124.39**
(5) Nonparametric panel t stats	-57.52**	-37.65**
(6) Parametric panel t stats	-657.16**	-313.54**
(7) group ρ statistics	-267.13**	-183.54*
(8) Nonparametric Group t stats	-58.08*	-43.96**
(9) Parametric group t stats	-57.94**	-43.00**

Row (1) represents Kao's ADF t-statistic which imposes a common Beta and first order autoregressive coefficient and is similar to a cointegrating Levin,.Lin, and Chu (2002) procedure. Row (2) is the Pedroni (1995) panel cointegration test, which also imposes a common coefficient on the slope and error, but has different assumptions regarding endogeneity. Rows (3)-(7) are the Pedroni (1999) panel cointegration tests that pool the autoregressive coefficients across firms and test a common coefficient, H_0: $\rho_i = 0\ \forall\ i$, versus H_1: $\rho_i = \rho < 0\ \forall\ i$. Row (3) is a non-parametric panel variance ratio test, while rows (4) and (5) are panel cointegration extensions of the non-parametric Phillips-Perron ρ and *t* statistics, and row (6) is a panel parametric *t* statistic (similar to a panel Engle-Granger ADF tests). Rows (7)-(9) are similar to rows (4)-(6) but allow for heterogeneity in the autoregressive coefficient. These procedures group or simply average the individually estimated coefficients for each industry *i*, and H_0: $\rho_i = 0\ \forall\ i$, versus H_1: $\rho_i < 0\ \forall$ for at least one *i*.

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Endnotes

[1] For pioneering work investigating the linkage between real wages and productivity using aggregate data for the UK see Hall (1986, 1989). He found a one-to-one linkage between real wages and productivity.

[2] For a more detailed discussion of some of these issues in the context of testing for purchasing power parity, see Breuer, McNown, and Wallace (2001) and Breuer, McNown and Wallace (2002).

[3]Although Maddala and Wu (1999) and Karlsson and Lothgren (2000) show that the power to reject is low when only a few series are stationary for the IPS (2003) procedure, the researcher is caught in a quandary concerning the interpretation of this finding. That is, it is possible to reject if a few stationary series occur in the data but also possible not to reject if most series are stationary. Accordingly, the alternative in the IPS procedure lacks inference concerning the prevalence/degree of stationary firms in the panel.

[4.] Some growth theory models augment labor with a parameter to depict labor saving technological change and write labor as $\Theta_t L$ in the production function. In that case, the (log) real wage would grow at the rate of labor productivity plus the growth rate of the labor saving technological change. There is disagreement in the literature as to whether such a factor (Θ_t) is stationary or a random walk.

[5] In our empirical analysis we allow for a non-constant labor share, α_2.

[6]Kao's website contains Gauss programs for the Levin and Lin (1993) and IPS (2003) panel unit root and cointegration tests as well as Pedroni's (1999) panel cointegration tests.

[7] The difference between Pedroni's group parametric-t test and Kao's procedure is that Pedroni's procedure, while allowing for heterogeneity in the cointegrating vector, potentially possesses an overly restrictive assumption concerning exogeneity between the regressors and error term; whereas, Kao's method restricts the long-run vector to be identical and corrects for weak exogeneity.

[8] The equation can be reparameterised and stacked as time series observations as follows:

$$\Delta y_i = \phi_i y_{i,-1} + X_i\beta_i + \sum_{j=1}^{p-1} \lambda_{ij}^{*}\Delta y_{i,-j} + \sum_{j=0}^{q-1} \Delta X_{i,-j}\delta_{ij}^{*} + \mu_i\varsigma + \varepsilon_i$$

where $i=1,2..N$, where $y_i = (y_{i1}\ldots,y_{iT})'$ is a Tx1 vector of observations of the dependent variable, $X_i = (x_{i1},..x_{iT})'$a *Txk* maxtrix of regressors that vary across inustries and time periods, and $\varsigma = (1,\ldots 1)'$ is a *Tx1* vector of ones. For further details on deriving the short-run and long-run coefficients, see Pesaran and Shin (1999).

[9.] Essentially, the system is overdifferenced when differencing each series yields a moving average.

[10.] Weak exogeneity implies that no information is lost, with respect to the parameters of interest, when one conditions on the variable(s) without explicitly modeling the variable(s). Strong exogeneity implies that the exogenous variable cannot be usefully forecasted or is not Granger-caused by the other variables in the system.

[11] If the error correction coefficient, $ec_{\Delta ulc}$, in the unit labor cost (ulc) equation is significantly different from zero, then there is long-run Granger causality, in that ulc adjust to disequilibrium between prices and ulc. If the error correction coefficient, $ec_{\Delta p}$, in the ulc equation is significantly different from zero, then there is long-run Granger causality, in that output price adjust to disequilibrium between prices and ulc .

[12] Recall from equation (12) that the significance of the t-statistics in Table I is determined through a one-sided normal distribution test. Applying equation (12) to the reported averaged t-values, we obtained a normalized t-statistic. The 1%, one-sided critical value from a normal distribution is -2.423.

[13] For example, consider normalization (1a). We subtract the ADF critical value of –2.02 (discussed above) from –2.89, divide by the standard error, and multiply by square root of N=459.

[14] The setup for the initial simulation is straightforward and follows McKoskey and Kao's (2001) procedure and our equations (13) and (14). Consider the cointegrating regression of Y on X in which the residuals (e_{it}) are then saved. A Dickey and Fuller (1979) test is conducted on these estimated residuals. Using the N-Dickey Fuller regressions, we construct a covariance matrix of the errors, v_{it}.

[15] Note that the specification of prices on ulc has a coefficient less than one, with an error correction coefficient of -.57. However, these results are only presented for information purposes, because the long run coefficient is biased due to normalization problems. Inspection of the individual regression also reveals that there are 20 industries with implausible error correction coefficients equal to -1.0.

[16] This value is the first moment for a regression with two right-hand side variables and is more negative than a bivariate regression. See Pedroni (1999).

[17] For ulc on p (p on ulc) 294 (201) industries have t-statistics that are substantially less than –2.453; for productivity on real wages (real wages on productivity) 285 (124) industries have t-statistics that are substantially less than –2.453.