Cointegration versus Traditional Econometric Techniques in Applied Economics

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INTRODUCTION

For more than a decade, cointegration techniques have been a dominant force in applied macroeconomics. Part of their attraction appears to be related to the conviction of many applied researchers that they play a useful role in identifying, with minimum prior theoretical analysis, long-run economic relationships that are buried in trended data. Cointegration techniques seem to be ideally matched with the many economic theories that are couched in long-run equilibrium terms (McKenzie, 1997). This match applies, a fortiori, to the analysis of growth issues that have moved to center stage in macroeconomics over the last ten years after having been on the sidelines for several decades.

Rather than supplying another survey of cointegration techniques (Muscatolesi and Hurn, 1992), this paper highlights some of the well-known problems with cointegration analysis in order to provide some perspective on the usefulness of cointegration techniques in applied economics. To better gauge the relative effectiveness of cointegration techniques, the paper compares them to traditional econometric time-series techniques of the autoregressive distributed lag type (ARDL) as summarized, for example, by Hendry et al. (1984). The comparison is based on a number of simple, easy-to-replicate Monte Carlo experiments with a widely used regression package (TSP 4.4).

The paper is organized as follows. The next section summarizes the basic idea of cointegration. The subsequent part details some key problems that cointegration analysis faces in economic applications. It also offers some numerical illustrations of these problems and a comparison to traditional econometric time-series techniques. The paper ends with a brief summary of the main points and their implications for using cointegration techniques.

THE ESSENCE OF COINTEGRATION

In what follows, cointegration is discussed independently of the available estimation techniques to focus on the idea of cointegration. Assume for that purpose that two variables, a variable y and a variable x, are of interest. Both variables are driven
by a stochastic trend and a random error. To be more specific, let $y_t$ be determined by the following two equations,

$$ y_t = \mu_t + \epsilon_t, \quad \epsilon_t \sim \text{NID}(0, \sigma_e^2), \quad t = 1, \ldots, T $$

and

$$ \mu_t = \mu_{t-1} + \eta_t, \quad \eta_t \sim \text{NID}(0, \sigma_\mu^2), \quad t = 1, \ldots, T, $$

where $\mu$ is a random walk, and where $\epsilon_t$ is a random error. The error term of the random walk ($\eta_t$) is assumed independent of the random error $\epsilon_t$.

Now consider variable $x_t$ which is driven, in complete analogy to $y$, by the following two model equations,

$$ x_t = \beta_1 \mu_t + \epsilon_t, \quad \epsilon_t \sim \text{NID}(0, \sigma_e^2), \quad t = 1, \ldots, T $$

and

$$ \beta_1 = \beta_{1-1} + \beta_1, \quad \beta_1 \sim \text{NID}(0, \sigma_{\beta_1}^2), \quad t = 1, \ldots, T, $$

where $\mu$ is a random walk, and where $\epsilon_t$ is a random error. The error term of the random walk ($\eta_t$) is independent of the random error $\epsilon_t$.

It is apparent that $y$ and $x$ follow stochastic trends. Both variables are non-stationary in levels but stationary in first differences or $I(1)$. The two variables $y$ and $x$ are cointegrated if the two random walk errors, $\eta_t$ and $\eta_t$, are linearly dependent; that is, if their correlation coefficient is unity. In practical terms, if the stochastic trend innovation for variable $x$ is $\alpha$ and the stochastic trend innovation for variable $y$ is a linear function of $\alpha$, then $x$ and $y$ are cointegrated. Another way of expressing this is to say that the two random walk errors have a common factor ($\alpha$). Linear dependence or a common factor among the two random errors implies that the rows (columns) of the variance-covariance matrix of the random walks $\mu$ and $\mu$ are linearly dependent. Hence, the covariance matrix is not of full rank. As is well known, this fact can be used to estimate the linear relationship between $x$ and $y$, which is also known as the cointegrating vector for $x$ and $y$.

As an extension, consider the case where the stochastic trend model for both $y$ and $x$ allows for a drift in the random walk that is driving the stochastic trend. The model for $y$ could then be written as

$$ y_t = \mu_t + \epsilon_t, \quad \epsilon_t \sim \text{NID}(0, \sigma_e^2), \quad t = 1, \ldots, T, $$

where the stochastic trend component is specified as

$$ \mu_t = \mu_{t-1} + \eta_t, \quad \eta_t \sim \text{NID}(0, \sigma_\mu^2), \quad t = 1, \ldots, T, $$

$$ \beta_1 = \beta_{1-1} + \beta_1, \quad \beta_1 \sim \text{NID}(0, \sigma_{\beta_1}^2), \quad t = 1, \ldots, T. $$

In this case, $\beta$ is the drift parameter of the random walk $\mu$. It is assumed to develop over time as a random walk itself. An analogous set of equations can be specified for $x$.

### Cointegration Versus Traditional Econometric Techniques

This case differs from the earlier one in that both $y$ and $x$ are integrated to order two rather than one. The first differences of $x$ and $y$ are cointegrated if the error terms that are driving the drift parameters in the two models are linearly dependent; that is, if they have a common factor. This, in turn, implies that the variance-covariance matrix of the error terms driving the drift parameters is of less than full rank.

The above description can be extended to more than two variables. Irrespective of the number of variables involved, cointegration remains to be tied to linear restrictions (common factors) among the random errors that drive the stochastic trends. However, what is different from the case of two variables is the number of linear dependencies (common factors) that may arise among the error terms. In the case of three variables, there may be two linear dependencies (common factors) and, therefore, two cointegrating vectors, and so forth for systems with more variables.

Further extensions of the basic model are possible to allow for cointegration of seasonal or cyclical components, as described, inter alia, by Engle et al. (1989) and Rohnjik and Franss (1996). Cointegration has also been extended to non-linear relationships (Granger et al., 1997). In all cases, however, cointegration reduces to common factors in the error terms that drive the respective stochastic processes.

What does the knowledge of cointegration and cointegrating vectors provide us with? First, the estimation of a multivariate system of cointegrated variables can make use of the reduced rank of the variance-covariance matrix, and will therefore raise the efficiency of the parameter estimates. Second, if one has predicted one of the variables in a cointegrated system, then the long-run trend values of the other variables can be derived using the cointegrating vector. But there is also something that cointegration techniques cannot provide. Since cointegration is a purely statistical concept, tied to common factors of stochastic disturbances, the technique does not guarantee that any of the common factors that may exist among the variables are economically meaningful. As a corollary, cointegration does not, by definition, imply that a component of the underlying economic structure has been identified.

### Some Practical Limitations of Cointegration Analysis

#### Cointegration Analysis When a Relationship is Spurious

Hardly any paper that used cointegration techniques for empirical exploration fails to mention why they use the cointegration methodology to avoid spurious regression results. That has been the key statistical motivation behind cointegration analysis since its inception. In practical applications, however, not all commonly used cointegration techniques have a unique edge over standard regression techniques in identifying spurious economic relationships. To illustrate this point, consider three independent random walks, $X, Y,$ and $Z$, with 99 observations each. By their construction, any association among them is purely spurious.

Let us assume that one approaches the association between $X, Y,$ and $Z$ in a traditional manner by starting out with a fourth-order autoregressive-distributed lag model (ADL) with $X$ as the dependent variable and tests this model down to a more parsimo-
TABLE 1

Unit Root Tests for Levels of Variables

<table>
<thead>
<tr>
<th></th>
<th>X</th>
<th>Y</th>
<th>Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>Augmented Dickey-Fuller</td>
<td>0.976</td>
<td>0.333</td>
<td>0.093</td>
</tr>
<tr>
<td>Phillips-Perron</td>
<td>0.97</td>
<td>0.333</td>
<td>0.093</td>
</tr>
</tbody>
</table>

Probability values (p-values) are provided for the null hypothesis of a unit root. See Note 2 in the text for the construction of the variables.

a. See Pantula et al. (1994).
b. p-values come from MacKinnon (1994).

One may arrive at a specification such as the following,

\[ X_t = -0.734 - 0.075 Y_{t-1} + 0.290 Z_t - 0.377 Z_{t-1} + 0.333 Z_{t-2} + 0.878 Y_{t-2} \]

\[ (-1.4) \quad (-1.5) \quad (1.87) \quad (-2.58) \quad (2.17) \quad (16.96) \]

\[ R^2 = 0.9036 \quad \text{p-value: td} = 0.82, \text{lag} = 0.85, \text{lag} = 0.32, \text{chow} = 0.19, \text{while} = 0.00, \text{reset} = 0.07 \]

where t-values are reported in parentheses below the estimated coefficients and where probability values (p-values) are provided for all statistical adequacy tests. The equation shows a surprisingly good statistical fit, with high R^2 and acceptable test statistics. In addition, the equation is dynamically stable. However, the equation lacks long-run economic content because the implied long-run multipliers (33% Z = 0.461 and 23% Y = -0.617) have t-values of 1.08 and -1.48, respectively, and are, therefore, not statistically significant at the five percent level.

Now consider a typical cointegration analysis of the relationship between X, Y, and Z. As is fairly standard practice, the analysis commences with unit root tests for all three variables. The results are given in Table 1. All three-unit root tests indicate that variable Y is I(1), but the evidence on the other two variables is less clear. Such ambiguity is fairly common for unit root tests. The analysis proceeds on the assumption that all three variables are I(1) as suggested by the first test reported in Table 1, which is arguably the most reliable of the three unit root tests [Pantula et al., 1994].

The tests for cointegration are next. The Engle-Granger procedure (Engle and Granger, 1987) cannot reject the null hypothesis of no cointegration among the three variables at any common level of statistical significance. This is the result that one would expect from a cointegration test on three independent random walks. By contrast, the Johansen (1991) cointegration trace test rejects the null hypothesis of zero rank (r = 0) with a p-value equal to 0.093 and the null hypothesis of rank one or less (r = 1) with a p-value equal to 0.023. Even testing at the one percent level results in

\[ W_r = 1.54 + 0.940 W_{r-1} - 0.695 W_{r-2} + 1.30 X_{r-1} - 2.03 X_{r-2} + 0.907 X_{r-3} \]

\[ (2.0) \quad (14.5) \quad (-0.54) \quad (3.07) \quad (-3.5) \quad (2.2) \]

Cointegration offers a powerful tool for economic analysis, allowing for a more comprehensive understanding of the relationships between economic variables. It is particularly useful in econometric modeling and forecasting, providing insights into the long-run dynamics of economic systems. The techniques discussed in this paper offer a valuable framework for researchers and practitioners looking to analyze and predict economic trends.
to a breakdown of cointegration analysis. In other words, the facts of economic reality fundamentally conflict with the statistical requirements of cointegration analysis.15

This fundamental contradiction is expressed in the large literature on structural breaks and how to handle them in cointegration analysis. Starting from early work by Perron [1989], and Hamilton [1990], to more recent contributions by Campos et al. [1996], Gregory et al. [1996], and Perron [1997], the problem of structural breaks has been subjected to intense scrutiny. Although the work in this area displays considerable ingenuity, it is generally based on the assumption that structural change is a rare occurrence in a world that is inherently stable. Experience in applied economics suggests the contrary: structural change is a permanent and key feature of economic reality. Not surprisingly, the work on cointegration and structural change16 appears to be moving ever closer to the same types of techniques, such as rolling regressions, that are commonplace in traditional time series econometrics. However, accepting the identification of cointegrating regressions that may only hold for certain, and possibly rather short, subsets of the data, effectively discards the spirit and basic idea of cointegration, which is to accept only relationships that survive the test of time. In that case, cointegration is starting to compete with methodologies that may be better suited to the type of structural change that is so common in economic applications.17

It may be noted that long time series cause a problem for cointegration analysis in applied economics not only because parameters vary, but also because data definitions are more likely to change. Such changes in definitions are not surprising. They reflect the changes to the structure of the economy. To illustrate the problem of structural change, consider the following relationship between W and X. For observations 2 to 30 the equation is assumed to be $W = 5 + 1.5 X + \epsilon$, where X is the random walk defined earlier and where the innovation $\epsilon$ is the one underlying the construction of random walk Y (Note 2). For observations 31 to 100, the equation is specified as $W = 8 + 1.2 X + \epsilon$. There is a structural break in the equation at observation 31 that changes both the intercept and the slope parameter.

Starting from a fourth-order ADL and testing down to a simpler form in the equation

$$W = 1.71 + 0.453 W_{t-1} + 0.290 W_{t-2} + 1.53 X_t - 0.950 X_{t-1} - 0.220 X_{t-2} \quad (3.2)$$

$$R^2 = 0.971 \quad p\text{-values: } td = .15, bg1 = .76, bg4 = .39, chow = .19, white = .05, reest = .01$$

where the implied long-run multiplier $\Delta W / \Delta X$ is equal to 1.40, with associated p-value equal to 0.00. A statistically significant long-run multiplier exists, but since the equation does not pass all statistical adequacy tests, the equation is not acceptable based on traditional regression methodology.

Consider now the cointegration methodology. Cointegration tests on W and X cannot reject the null hypothesis of no-cointegration for either the Engle-Granger (p-value = 0.86) or the Johansen technique (p-value = 0.17) at the five percent level of significance. Again, the standard cointegration methodology does not indicate a lack of cointegration.
The above experiment is repeated 1,000 times to get a better idea of how the structural break affects traditional regression methodology versus cointegration analysis. For the particular example at hand, the Engle-Granger and Johansen techniques reject the null hypothesis of no-cointegration at the five percent level 17 and 76 percent of the times, respectively. For an unrestricted fourth-order ADL, a statistically significant long-run multiplier is found in 95 percent of all cases. However, at least one of the statistical adequacy tests signal rejection of the model assumptions in all cases at the five percent level of significance.

The Monte Carlo evidence supports our earlier work that a structural break can fairly easily lead to the conclusion of no-cointegration for the Engle-Granger methodology. By contrast, the Johansen technique appears to be less affected by a structural break. How to evaluate this empirical evidence is not clear cut. The finding of no-cointegration is undesirable because there is a meaningful underlying relationship, albeit one with a structural break. However, rejection of the null of no-cointegration is also undesirable because it leaves the researcher with a cointegrating vector that is not correct and with no indication that something may be wrong with it.

The traditional regression techniques provide a more useful outcome. They correctly identify the existence of a statistically significant long-run relationship. Yet, at the same time, they signal that the equation has a statistical problem, which forces the conscientious researcher to investigate further. In a sense then, the traditional approach offers a more constructive modeling environment than standard cointegration techniques.

The Problem of Simultaneity. If the variables that form part of the cointegration analysis are simultaneously determined in the sense of the Cowles Commission, then cointegration analysis may have little to offer relative to such venerable techniques as two-stage least squares. In fact, Hsiao [1993; 1997b] has shown that in the context of dynamic simultaneous equation systems and no identification problem one can all but ignore the time series properties of the variables and instead use the received techniques without being worse off.

To illustrate this point, consider the following linear dynamic simultaneous equations system consisting of two behavioral equations (demand and supply, respectively) and an equilibrium condition:

\begin{align*}
Q_t^d &= 1 + 0.5P_t + 0.5Y_t + 2Z_t + 0.2Q_{t-1} + u_t \\
Q_t^s &= 1 + 0.5P_t + X_t + 0.8Q_{t-1} + v_t \\
Q_t^e &= Q_t^d = Q_t^s
\end{align*}

where the variables \( Y, Z, \) and \( X \) are random walks defined earlier, \( u \) and \( v \) are standard normal random variables, and \( Q \) and \( P \) are generated on the basis of the associated reduced-form equations.

Cointegration techniques are examined for this system under two alternative assumptions: (a) the structure of the system outside of its dynamics is known to the researcher and (b) nothing is known to the researcher outside of the variables that play a role in the system. It must be noted that the traditional Cowles Commission approach and the work of Hsiao [1993a; 1997b] assume that the structure of the system is known, at least approximately. Hence, assumption (b) is irrelevant for the traditional approach.

Table 2 reports the results of the Engle-Granger and Johansen cointegration tests on the variables of each equation, but excluding the lagged dependent variable. At the five percent level of significance, the Engle-Granger technique identifies a cointegrating vector only for the demand function. The Johansen technique finds multiple cointegrating vectors for the demand function. Both OLS and 2SLS estimates are based on an unrestricted second-order ADL, true to the assumption that the dynamics of the equations are unknown. Both techniques identify the existence of long-run parameters at better than the one percent level for all variables. Comparing the estimated long-run parameters to the true ones, it is apparent that both OLS and the Engle-Granger technique have the largest bias. The first cointegrating vector of the Johansen technique and the 2SLS method tend to provide better long-run parameter estimates.

The above experiments are repeated 1,000 times. For each replication, the random walks \( X, Y, \) and \( Z \) and the disturbance terms \( u \) and \( v \) are created from a new set of innovations. At the five percent level of significance, the Engle-Granger technique
identifies a CIV for the demand function in 74.4 percent of all cases. This contrasts with 93.5 percent for the Johansen technique. For the supply function, the Engle-Granger technique finds a CIV in only 2 percent of all cases, while the Johansen technique does so in 99.3 percent of all cases. In 44 percent of all cases, the Johansen technique finds a second CIV for the demand function. For the supply function, the percentage is about 23 percent. 2SLS establishes the existence of a long-run multiplier for each of the five variables in about 92 to 98 percent of all cases when the test is conducted at the five percent level.

What is perhaps most interesting for these experiments is a comparison of how close the long-run parameter estimates of the Johansen technique and 2SLS are to their true values. For each replication, the better of the two estimation techniques is identified on the basis of the absolute deviation of the long-run parameter estimates from their true value, summed over all five parameters. The 2SLS technique outperforms the Johansen technique by this criterion for 69.3 percent of the 1,000 replications. These results support the point made by Reins (1997b); if there is no specification uncertainty with regard to which variables enter the equations to be estimated, there is little to recommend cointegration techniques over a dynamic version of 2SLS.

According to assumption (b), specification uncertainty implies that the researcher knows the variables that enter the system of equations but does not want to assign the variables to the structural equations or to distinguish between endogenous and exogenous variables. A fairly common approach to cointegration testing in this context is to use all variables \( Q, P, X, Y, Z \) in the cointegration analysis. The results of such an exercise for the variables used at the beginning of this section are presented in Table 3. Again, multiple CIVs arise for the Johansen technique, none with any obvious economic interpretation. This suggests the existence of an identification problem. The way to proceed in this case would be to impose and test identifying restrictions as discussed, inter alia, by Johansen (1988) and Boswijk (1996). It requires no further discussion that economic theory is needed to deliver these identifying restrictions. Hence, it is again obvious that cointegration analysis needs a sufficient foundation in terms of economic theory to make economic sense.

A simple way to produce identification restrictions may sometimes be to impose exclusion restrictions covering either single or multiple variables. Recently, Davidson (1998) has taken the idea of exclusion restrictions and reformulated it as a search for \textit{irreducible cointegrating relations} (ICRs). From a practical point of view, such a search implies testing all possible subsets of variables for cointegration. All subsets of variables that cointegrate belong to the set of ICRs. All supersets that also cointegrate are discarded as are all variable sets that do not cointegrate. As discussed in detail in Davidson (1998), this simple elimination procedure can potentially identify structural economic relationships and other useful relationships, such as reduced forms. This is borne out for the given data set (Table 3). Davidson’s (1998) methodology has little trouble identifying the two structural equations and the two corresponding reduced-form equations in the current data. This is a notable advance beyond the unrestricted and uninterpretable CIVs identified by the Johansen technique. However, it needs to be kept in mind that Davidson’s (1998) methodology is not immune to the problems discussed earlier. The omission of important variables in the original set of variables, structural change, and collinearity among the set of variables will negatively affect the methodology, as they will all cointegration techniques.

### SUMMARY AND CONCLUSIONS

The purpose of this paper has been to provide some perspective on the usefulness of cointegration techniques in applied economics. This has been accomplished by (1) reviewing the weak spots of cointegration analysis and (2) comparing the performance of two popular cointegration techniques to the traditional autoregressive distributed lag model.

The comparison of cointegration and traditional econometric time-series techniques suggests two conclusions. First, traditional econometric techniques have not become completely obsolete for trended data as it is sometimes suggested. In fact, for many applications they offer a sensible alternative to cointegration techniques. Second, cointegration techniques need to be applied with great care. This latter conclusion has at least three dimensions. First, cointegration analysis is not a substitute for carefully developing the underlying economic theory. In particular, approaching cointegration analysis with the type of minimal economic theory that may be suffi-
cient for short-run VAR forecasts is likely to lead to an omitted variables problem, multiple co-integrating vectors, and incorrect inferences. Second, every researcher needs to be aware of the fact that standard co-integration techniques do not work very well for the long time series for which they are intended because of the ever present possibility of structural change in the economic environment. Third, if one or more co-integrating vectors are identified, it is highly desirable to test for identifying and/or exclusion restrictions. The procedure developed by Davidson (1998) appears to be well suited for many practical applications because it allows one to derive, in a systematic manner, co-integrating vectors with potentially sensible economic interpretations.

NOTES

The author wishes to thank the Faculty Research and Creative Activity Committee at Middle Tennessee State University for financial support.

1. McNew and Fackler (1997) present a recent example in which co-integration has no obvious relation to economic theory.
2. The series are created in TSP 4.4 for observations 2 to 100, with sample observation 1 being zero for all three series: Standard normal random variables are used for their construction. The random walks X, Y, and Z are generated for the sample 2 to 100, with the following seeds for the respective error terms (starting with observation 1): e₁ = 12366, e₂ = 87943, e₃ = 64934.
3. It is assumed that a simple regression in levels will not be seriously untoward. Such an exercise would lead to a high R² (0.8520) but highly significant statistics for autocorrelation, structural break, and functional form tests.
4. The difference in φ stands for a likelihood ratio test of the exclusion restrictions relative to a fourth-order ARDL lag and φ₄ represents the Breusch-Godfrey test (Breusch, 1978) for autocorrelation with one and four lags, respectively; χ₄ identifies Chow's (1960) test for structural break at the sample midpoint; white's (1960) test for heteroscedasticity, and ρ₄ stands for Ramsey's (1969) test for functional form misspecification.
5. Asymptotic t-values are calculated by the delta method. The qualitative conclusions do not change if one does not test down the fourth-order ARDL in a more parsimonious form but calculates asymptotic t-values for the equation containing all four lags.
6. Unit root tests are repeated on the first differences of X, Y, and Z, and if and reject the null of non-stationarity at all reasonable levels of statistical significance for all these variables.
7. The associated χ₄ value is 0.436 with two lags added.
8. The unemployment estimation procedure is the one hard-programmed in TSP 4.4. An AIC rule is used for the optimal lag length. Finite sample corrections are applied according to Gregory (1994), and p-values are interpolated from Osterwald-Lenum (1992).
9. Very similar results can be found in Gonzalo and Lee (1995).
10. Fewer significant signs are typically found when the ADL is tested down to a more parsimonious form.
11. Note 2 discusses the construction of variable X and innovation φ₄.
13. Prior to this, it would appear that there were fewer conflicts in the natural sciences where the vast majority of relationships analyzed did not change over time.
14. See Mandala and Kim (1998, Chapter 13) for a recent survey and assessment of this work on the identification and structural change.
15. Such a methodology is structural time series modeling, also known as unobserved components modeling (Harvey, 1989, 1997).
16. Random variable u is generated with seed 2372 and random variable v with seed 32322 in TSP 4.4.
17. If the model specification is only approximately known, the traditional approach would use (1) statistical adequacy tests, (2) tests for the existence of economically sensible long-run multipliers, and (3)
TEACHING NOTE:

LET’S STOP PROFESSING THAT THE LEGAL INCIDENCE OF THE SOCIAL SECURITY TAX IS IRRELEVANT

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and

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The division of the legal incidence of the Social Security tax has a long history and is a consequence of our lawmakers’ feeling that the payroll tax should be shared equally by employers and employees. It is important to realize that the statutory distinction between workers and bosses is irrelevant. As suggested earlier, the incidence of this labor tax is determined only by the wedge the tax puts between what employees receive and employers pay.

Harvey Rosen [1985, 385; italics in the original]

Whenever Social Security taxes are raised, there is a furor in the legislature about how to divide the legal incidence... [Should the taxes] be paid entirely by employees, entirely by firms, divided equally or divided in some other way?... The resolution ultimately makes not one bit of difference to anybody.

Steven E. Landsburg [1995, 26-27]

INTRODUCTION

Economists have long argued that a tax’s legal incidence is irrelevant for its economic incidence. Textbook authors frequently use the U.S. Social Security levy to explain this proposition. The frequency probably traces to the “faireness” contested by the levy’s 50:50 split in legal incidence between employers and employees. Economists delight in popping “fairness” balloons.1

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