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Measuring and Analyzing Aggregate Fluctuations: The Importance of Building from Microeconomic Evidence

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A pervasive finding in recent research using longitudinal establishment-level data is that idiosyncratic factors dominate the distribution of output, employment, investment, and productivity growth rates across establishments.[1] Seemingly similar plants within the same industry exhibit substantially different behavior on a variety of measures of real activity at cyclical and longer-run frequencies. In the fastest-growing industries, a large fraction of establishments experience substantial declines, whereas in the slowest growing industries, a large fraction of establishments exhibit dramatic growth. During severe recessions virtually all industries decline, but within each industry a substantial fraction of establishments exhibit substantial growth. Likewise, during robust recoveries, a substantial fraction of establishments are contracting. Simply put, the underlying gross microeconomic changes in activity dwarf the net changes we observe, based on published aggregates.

Table 1 provides a simple characterization of the dominance of within-sector factors in accounting for variation in growth rates across establishments. Table 1 is based on the computation of establishment-level growth rates during a 10-year period for employment, capital stocks, output, labor productivity, and total factor productivity for plants that appear in both the 1977 and 1987 Census of Manufactures. As indicated in Table 1, four-digit industry effects account for less than 10 percent of the cross-sectional variation in growth rates across continuing establishments for each of these measures.

The observed tremendous within-sector heterogeneity raises a variety of questions for our understanding and measurement of key macro aggregates. Much of macroeconomic research and our measurement of aggregates is predicated on the view that building macro aggregates from industry-level data is sufficient for understanding the behavior of the macroeconomy. The implicit argument is that, at least at the level of detailed industry, the assumption of a representative firm or establishment is reasonable.

Table 1

Fraction of Variance of Establishment-Level Growth Rates: Four-Digit Industry Effects

Dependent Variable	R^2
Employment growth	0.057
Capital equipment growth	0.062
Capital structures growth	0.052
Output (gross) growth	0.089
Labor productivity growth (gross output per hour)	0.086
Total factor productivity growth	0.095

SOURCE: Tabulations from Longitudinal Research Database (LRD). Reported results are based on computed 10-year growth rates for establishments present in both the 1977 and 1987 Census of Manufactures (CM). For such continuing establishments, the reported R^2 is based on the regression of the establishment-level growth rate for the indicated measure on four-digit industry fixed effects. See Appendix for discussion of the measurement of each of these indexes at the establishment level.

The finding of tremendous within-industry heterogeneity is not by itself sufficient to justify abandoning this useful assumption. As Lucas (1977) eloquently

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[1] References and detailed discussion of selected studies are provided in the section entitled "Micro Heterogeneity and Aggregate Fluctuations: A Brief Review of Recent Evidence."

argues in defense of representative agent models, there is undoubtedly considerable cancelling out of the impact of idiosyncratic shocks (e.g., taste, cost, and technology) that underlie the heterogeneous fortunes across individual producers. However, the accumulating evidence from recent establishment-level studies of employment, investment, and productivity growth suggests that this canceling out is far from complete. It is becoming increasingly apparent that changes in the key macro aggregates at cyclical and secular frequencies are best understood by tracking the evolution of the cross-sectional distribution of activity and changes at the micro level.

A number of different factors are potentially important in this context. The observed heterogeneity in output, employment, and investment growth rates within sectors implies a large, continuous pace of reallocation of real activity across production sites. Such reallocation inherently involves substantial frictions. An obvious and important friction is that it is time- and resource-consuming for workers (and for other inputs) to reallocate across production sites. High- and low-frequency changes in key macro aggregates are likely associated with the interaction of these frictions and the pace of reallocation. The level of unemployment, as well as the growth rate of aggregate measures of real activity (e.g., real output or productivity), will reflect the efficiency of the economy in accommodating the pace of reallocation. Changes in institutions, regulation, the pace of technological change, and the sectorial mix of activity are all factors that may alter the intensity of reallocative activity and the economy's ability to accommodate the reallocation.

In a related manner, it is important to consider the nature of the adjustment costs at individual production sites in changing the scale and scope of activity. Accumulating empirical evidence of lumpy microeconomic adjustment of inputs like employment and capital suggests the presence of nonconvexities in micro-adjustment costs or, at the minimum, it implies highly nonlinear adjustment at the micro level. Nonlinear micro adjustment in combination with micro heterogeneity have important implications for aggregate fluctuations. One key implication is time-varying elasticities of aggregates with respect to aggregate shocks. Roughly speaking, time-varying elasticities arise in this context because the impact of an aggregate shock depends on the distribution of where individual producers are with respect to their adjustment thresholds. Viewed from this perspective, characterizing aggregate fluctuations requires tracking the evolution of the history of the distribution of shocks and adjustments.

In the context of these heterogeneity and aggregation issues for aggregate fluctuations, this article has two related objectives. The first objective is to quantify and assess the empirical importance of these heterogeneity and aggregation issues. The empirical questions to be evaluated include: Where, when, and how much do these heterogeneity and aggregation issues matter for aggregate fluctuations? I address these questions by summarizing and extending the recent empirical evidence, using establishment-level data. This evidence is primarily based on research which uses the Longitudinal Research Database (LRD), which is based on the longitudinal linkage of establishment-level data from the Annual Survey of Manufactures (ASM) and Census of Manufactures (CM). As such, the evidence presented is primarily restricted to the U.S. manufacturing sector.

My second objective is, in light of this evidence, to provide some guidance regarding the collecting and processing of data on real activity by the U.S. statistical agencies. In considering the second objective, it is important to emphasize that the measurement of key aggregates like real output growth and productivity growth are generated from myriad data sources linked at an aggregate level (e.g., commodity or industry). The individual ingredients underlying these measures (i.e., nominal receipts or shipments, inventories, prices,

intermediate inputs, capital stocks, capital expenditures, labor, wages, rental prices) are derived from a variety of statistical and federal agencies' surveys and economic censuses of establishments and companies. As emphasized in the recent literature, the quality of the measurement varies widely across industries.[2] The variation in quality is partly a result of the substantial differences in the nature and coverage of the surveys across sectors and partly because of a number of unresolved conceptual issues in the measurement of output and inputs for some sectors. However, even for the best-measured sectors (e.g., manufacturing) the information underlying published aggregates (e.g., real output or productivity growth) are based on matching information from a variety of different sources at an industry level. The United States does not currently collect data on the activities of the business population in a comprehensive, integrated manner. The implication is that building the requisite micro databases necessary to incorporate these heterogeneity and aggregation issues in the analysis of aggregate fluctuations is for most sectors currently difficult, if not impossible. With this in mind, I consider the possibilities and practicalities of the data development required to pursue these objectives.

MICRO HETEROGENEITY AND AGGREGATE FLUCTUATIONS: RECENT EVIDENCE

Employment Dynamics

Job Creation and Destruction. Much of the recent empirical analysis documenting and analyzing the connection between micro heterogeneity and aggregate fluctuations has focused on employment dynamics. One reason for this is that many of the frictions involving establishment-level adjustment and the reallocation of real activity across production sites involves workers. A second reason is based on data constraints. Establishment-level surveys, censuses, and administrative record databases typically include employment.[3]

Table 2

Estimates of Average Job Creation and Destruction Rates*

Dataset (Sector)	Period	Job Creation	Job Destruction
Annual			
LRD (mfg)	1972-93	8.7	10.1
CWBH (all)	1979-83	11.4	9.9
CWBH (mfg)	1979-83	10.2	11.5
CWBH (services)	1979-83	10.6	8.7
UI-Michigan (all)	1978-88	10.0	9.6
UI-Michigan (mfg)	1978-88	6.2	8.5
UI-Michigan (services)	1978-88	15.6	11.0
Quarterly			
LRD/MTD (mfg)	1947:1-88:4	6.0	6.0
CWBH (all)	1978:3-84:1	7.1	6.4
CWBH (mfg)	1978:3-1984:1	5.8	6.2
CWBH (services)	1978:3-1984:1	7.9	6.7

*As Percentages of Employment

SOURCE: LRD tabulations from Longitudinal Research Database based on methodology in Davis, Haltiwanger, and Schuh (1996). CWBH tabulations from the Continuous Worker and Benefit History files for six states, reported in Anderson and Meyer (1994). UI-Michigan tabulations of unemployment insurance record database reported in Foote (1995). LRD/MTD tabulations from spliced data from LRD and BLS Manufacturing Turnover Data (MTD) as reported in Davis and Haltiwanger (1996).

Furthermore, employment at the establishment is measured reasonably accurately and typically not imputed. Thus, in terms of coverage across sectors and time, establishment-level employment data are the most plentiful and are of reasonable quality.

The evidence summarized here is based primarily on the decomposition of net employment growth into job creation and destruction. Job creation is defined as the sum of employment gains at expanding and new establishments. Job destruction is defined as the sum of employment losses at contracting and closing establishments. Table 2 provides some summary statistics from studies tabulating job creation and destruction rates at annual and quarterly frequencies from a variety of different sources. In manufacturing (the sector with the most readily available establishment-level data for the longest period), annual job creation and destruction rates

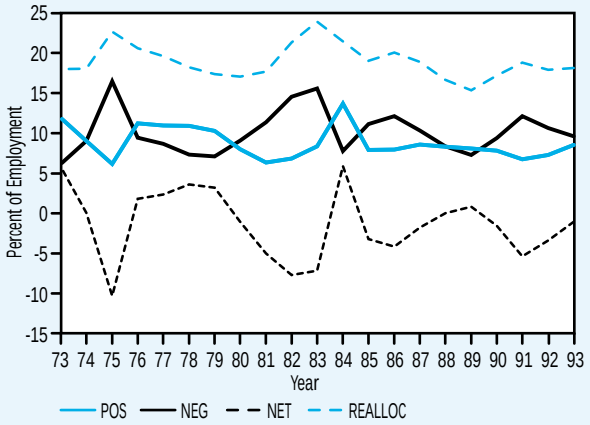
[2] See, for example, Griliches (1994) and Gordon (1996).

[3] In the discussion that follows, the distinction between establishments and companies (a distinction that macroeconomists do not typically emphasize or appreciate) is vital. Establishments are economic units at a single physical location where business is conducted or where services or industrial operations are performed. Companies are one or more establishments (e.g., General Motors) owned by the same legal entity or group of affiliated entities.

Figure 1

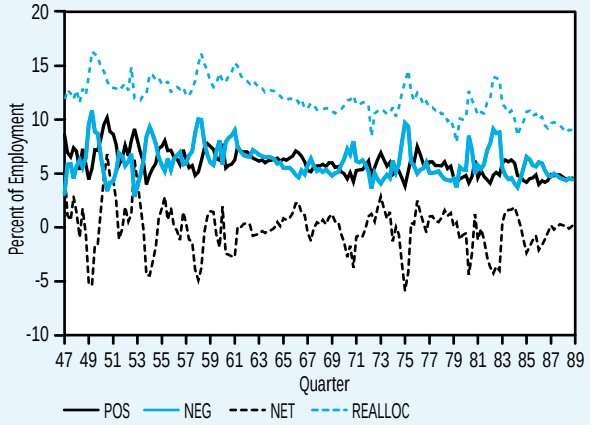
Net and Gross Flow Rates in Manufacturing

Annual, 1973 to 1993



SOURCE: Tabulations from the LRD.

Quarterly, 1947:1 to1988:4



SOURCE: Davis and Haltiwanger (1986).

are large in absolute magnitude. Roughly 1 in 10 manufacturing jobs is created in a typical year, and 1 in 10 jobs is destroyed in a typical year. In nonmanufacturing (with spottier information based on tabulations from selected states for relatively short sample periods), job creation and job destruction rates are on average slightly higher. Quarterly job creation and job destruction rates average around 6 percent in manufacturing and somewhat higher in nonmanufaturing.[4]

The large pace of implied job reallocation (measured as the sum of job creation and job destruction) in both manufacturing and nonmanufacturing sectors highlights the remarkable fluidity in the distribution of job opportunities across locations in the U.S. economy. Much of this fluidity reflects shifts within narrowly defined sectors, rather than between sectors. For example, Davis, Haltiwanger, and Schuh (1996) calculate that only 13 percent of job reallocation in manufacturing reflects shifts of employment opportunities between four-digit sectors.[5]

One important issue for the relevance of these statistics for aggregate fluctuations is the nature of time-series variation in the pace of job reallocation. The top panel of Figure 1 depicts the annual rates of job creation (POS), job destruction (NEG), net employment growth (NET), and job reallocation (REALLOC) for the U.S. manufacturing sector for the period 1973-93. The bottom panel depicts quarterly rates of job creation, job destruction, net employment growth, and job reallocation for the U.S. manufacturing sector for the period 1947:1-88:4.[6] In U.S. manufacturing, the pace of job reallocation varies systematically throughout the cycle at annual and quarterly frequencies. During downturns, job reallocation in manufacturing rises. The countercyclical job reallocation reflects the asymmetric patterns of job creation and destruction throughout the cycle. Although job creation is procyclical and job destruction is countercyclical, much of the cyclical variation in net employment growth is driven by the greater cyclical volatility of job destruction. The lower panel of Figure 1 indicates that this pattern holds for the U.S. manufacturing sector for the entire post-World War II (WWII) period, although the pattern is more pronounced in the 1970s and the 1980s.[7]

In terms of secular changes, the annual 1973-93 data reveal no obvious trend in the pace of job reallocation. This in itself is striking, given recent concerns in the popular press about rising job insecurity.[8] The quarterly data do not yet extend into the 1990s but offer a depiction of job-flow dynamics during a much

[4] By comparing the quarterly rates with the annual rates, it is clear that many workers experience repeated transitions during the year or transitions that are reversed within the year. Davis, Haltiwanger, and Schuh (1996) characterize the relative persistence of job creation and destruction rates.

[5] This calculation is based on a decomposition of excess job reallocation that is measured as total job reallocation less the absolute value of net

longer period. The pace of job reallocation shows a mild downward trend throughout 1947:1-88:4. An interesting aspect of this trend is that it is primarily accounted for by a mild downward trend in the pace of job creation. Thus, in contrast to the cyclical changes in net employment growth, the very low-frequency changes in net employment growth in U.S. manufacturing appear to be driven more by changes in the rate of job creation than in the rate of job destruction.

Even modest frictions in the face of the observed magnitude and time-series variation of job reallocation are likely to yield important implications for aggregate fluctuations. The aggregate implications of these job flows for unemployment-rate dynamics have recently been investigated by Hall (1995). Hall develops a framework in which a burst of job destruction begets further job separations. Workers whose jobs are destroyed seek new matches, and, by their very nature, new matches are subject to higher match termination rates than the typical match. Hall's analysis provides some quite striking empirical evidence on these dynamics, showing that an impulse in job destruction yields persistent rebuilding of employment relationships for several periods. For example, he finds that an impulse in quarterly job destruction yields persistently higher inflows into unemployment via permanent layoffs for eight quarters.

Hall's findings suggest that the process whereby permanent job destruction begets further employment losses for several quarters may be an important part of the persistence that we observe for aggregate fluctuations; there is no shortage of explanations for this persistence. But these explanations have been generally viewed as unsuccessful or incomplete because they can only account quantitatively for relative short recessions. Although this approach looks promising in terms of accounting for recessions that persist for significant periods, a number of questions remain. Of particular interest here is why we observe the burst of permanent (and it is important to emphasize the permanent component for Hall's story) job destruction at the onset of recessions. In recent years, some economists have begun developing theories to explain the magnitude and cyclical behavior of job (and worker) flows and the connection to aggregate fluctuations. Two types of theories have received the most attention.[9] One type treats fluctuations over time in the intensity of allocative shocks as an important driving force behind aggregate fluctuations. The second type maintains that aggregate shocks are the primary driving forces underlying business cycles but that the propagation of aggregate shocks involves intertemporal substitution effects changing the incentives for the timing of reallocation. For this article's purposes, the important debate about the direction of causality and thus the relative contribution of aggregate and allocative disturbances are not important.[10] The relevant point here is that understanding aggregate fluctuations requires tracking the evolution of the distribution of microeconomic changes.

Nonlinear Micro Adjustment. The discussion thus far has focused on the aggregate consequences generated by the resource and time-consuming nature of reallocation. A closely related issue is that the adjustment at the individual producer level may be nonlinear. For example, Davis, Haltiwanger, and Schuh (1996) report that about two-thirds of annual job creation and destruction are accounted for by establishments with growth rates in excess of 25 percent in absolute magnitude. Of this, plant start-ups account for 12 percent of annual job creation, while plant shutdowns account for about 23 percent of annual job destruction. Thus, the distribution of establishment-level employment changes exhibits both considerable heterogeneity and fat tails. The lumpy changes at the micro level in combination with the heterogeneity in turn have consequences beyond those discussed earlier.

Building on the literature about the aggregation of (*S*,*s*) models, a useful means of organizing micro data to characterize the interaction of nonlinear micro adjust-

employment growth. See Table 3.8 in Davis, Haltiwanger, and Schuh (1996), for further details and discussion.

[6] The top panel of Figure 1 is based on tabulations from the LRD, extending the methodology for generating annual job flow statistics developed by Davis, Haltiwanger, and Schuh (1996). The lower panel of Figure 1 is based on splicing job creation and job destruction statistics generated from the Bureau of Labor Statistics (BLS) manufacturing turnover data along with the quarterly statistics from Davis, Haltiwanger, and Schuh tabulated from the LRD. The methodology for using the BLS manufacturing data and splicing with the LRD series is discussed in detail in Davis and Haltiwanger (1996).

[7] The recent analysis by Foote (1995) suggests that the cyclical patterns of job creation and destruction in nonmanufacturing sectors are different than those observed in manufacturing.

[8] More direct evidence that overall job security has not diminished in recent years can be found in Farber (1995).

[9] See Blanchard and Diamond (1989, 1990), Caballero (1992), Caballero and Hammour (1994), Campbell (1995), Davis and Haltiwanger (1990), Hall (1991), and Mortensen and Pissarides (1994) for examples of recent models investigating these issues.

[10] See Blanchard and Diamond (1989, 1990), Caballero, Engel, and Haltiwanger (1997), Campbell and Kuttner (1996), and Davis and Haltiwanger (1990, 1996) for

ment and heterogeneity has recently been developed by Caballero and Engel (1992, 1993). For employment (or as we will see later in a similar specification for capital adjustment), the relationship between micro adjustment, micro heterogeneity, and aggregate fluctuations can be summarized in the following simple equation:

$$(1) \qquad \Delta E_t = \int x A(x,t) f(x,t) dx,$$

where in this case the left side measures aggregate employment growth, x is the deviation between desired and actual employment for an individual producer (i.e., "shortages" that can be positive or negative), $f(x,t)$ is the cross-sectional distribution of shortages across producers, and $A(x,t)$ is the adjustment-rate function.[11] The latter measures the fraction of the shortage that producers with shortage x close on average in period t.[12]

This simple specification accommodates a wide variety of alternative characterizations of adjustment. The partial adjustment model is characterized by setting $A(x,t)$ to a constant. In this special but well-known case, only first moments of the distribution of shortages matter for aggregate employment growth. This case yields the familiar expression that aggregate employment growth can be expressed as a function of the deviation between an aggregate measure of desired and actual employment. More generally, a nonlinear $A(x,t)$ [e.g., that generated by an (S,s) model] yields that higher moments of x are important for characterizing aggregate fluctuations. For example, suppose $A(x,t) = \lambda_0 + \lambda_2 x_t^2$, with $\lambda_0 > 0$ and $\lambda_2 > 0$ so that Equation 1 can be expressed as:

$$(2) \qquad \Delta E_t = \lambda_0 \mu_x(t) + 3\lambda_2 \mu_x(t)\sigma_x^2(t) + \lambda_2 \mu_x^3(t) + \lambda_2 \sigma_x^3(t)\gamma_x(t),$$

where $\mu_x(t)$, and $\sigma_x(t)$, and $\gamma_x(t)$ denote the mean, standard deviation, and skewness coefficients of the cross-sectional distribution of employment shortages at time t. In this simple example, higher moments of the cross-sectional distribution of shortages affect the evolution of aggregate employment through mean-variance and variance-skewness interaction terms. It is also the case that the first moment affects aggregate dynamics in a nonlinear fashion, which is at the heart of the time-varying elasticities with respect to aggregate shocks (discussed below).

The attractive feature of this semi-reduced form specification is that, conditional on generating a measure for x (quite an exercise), this specification permits a completely flexible characterization of the empirical microeconomic adjustment function with micro data, permitting measurement of x. In addition, conditional on a measure of x, the above specification yields an exact decomposition of aggregate employment fluctuations into the contribution of changes in the adjustment-rate function and the cross-sectional distribution of shortages.[13]

This specification has been recently used with the establishment-level quarterly data on hours and employment from the LRD by Caballero, Engel, and Haltiwanger (1997) (hereafter CEH, 1997) for the period 1972:1-1980:4.[14] An important issue is how to measure the deviation between desired and actual employment for an individual establishment. CEH (1997) implement a specification in which the deviation between desired and actual employment is proportional to the deviation between actual hours per worker and "normal" hours per worker at the establishment. "Normal" hours is measured as the average hours per worker during the sample period at each plant. The specification is motivated by models developed by Bils (1987) and Caballero and Engel (1993) in which it is assumed that technology and wage schedules are such that if plants did not face costs of adjusting their level of employment, they would keep the same number of hours per worker. However, if costs of adjusting employment are larger—at least in the short run—then hours per worker will be positively correlated with the degree of a plant's employment shortage.

studies that attempt to use worker and job flows to quantify the relative contribution of aggregate and allocative disturbances for aggregate fluctuations.

[11] The measure of aggregate employment growth here is in fact average (across establishments) employment growth. See Cabellero, Engel, and Haltiwanger (1997) for further discussion of this issue.

[12] This specification is silent on the distribution of micro adjustments underlying the average rate of adjustment across producers at a given value of x. For example, a rate of adjustment of 0.5 at a given value of x could be driven by all establishments adjusting by 50 percent of x or by half of the establishments exhibiting complete adjustment and half zero adjustment. The results in Caballero, Engel, and Haltiwanger (1997) suggest that the latter bimodal distribution of adjustments is a closer approximation to reality for employment adjustment.

[13] An alternative approach taken by Caballero and Engel (1993) for employment growth and Caballero and Engel (1994) for investment dynamics is to specify functional forms for the adjustment-rate function and the distributions of the shocks underlying time-series variation in the cross-sectional distribution. Under suitable restrictions, the parameters of the relevant adjustment function and distributions can be identified and estimated using aggregate data.

[14] A balanced panel of approximately 10,000 large continuing establishments is used for this analysis.

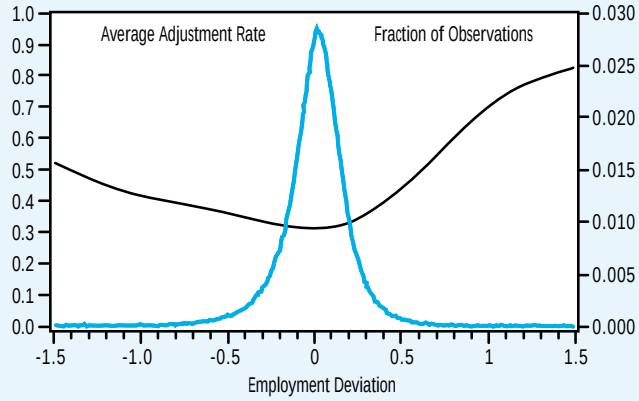
Although this specification can be theoretically justified, the 1972:1-1980:4 sample period and the use of hours per worker to construct the measure of x are dictated by data limitations. As Hamermesh (1993) emphasizes, for analysis of the nature of lumpy microeconomic adjustment of employment, it is important to use high-frequency data since employment decisions are undoubtedly made more often than annually. In the LRD the only quarterly variables collected are hours and employment and, as of 1980:4, the quarterly hours data were no longer collected. In the section entitled "Implications for Data Collection, Processing, and Measurement," I return to the issues relating to the fact that this approach to aggregation and heterogeneity naturally requires establishment-level information on more than one variable.

The key finding in CEH (1997) is that the adjustment-rate function is highly nonlinear. Figure 2 depicts the average (over time) adjustment-rate function, along with the average (over time) cross sectional distribution from this analysis.[15] Establishments are more likely to react (or react by more) to large employment shortages than to small ones. For example, on average, about 70 percent of a 10 percent shortage remains one quarter later, while only 50 percent of a 60 percent shortage remains one quarter later. The average cross-sectional distribution provides another view of the tremendous heterogeneity in the fortunes across individual producers. It does show, however, that establishments spend a large fraction of their time within plus or minus 30 percent of their desired employment level.

The micro nonlinear adjustment function implies that higher moments matter for aggregate fluctuations. Two results from CEH (1997) help quantify the aggregate significance of this microeconomic nonlinearity. First, CEH consider the impact of adding higher moments of measures of x, relative to a standard aggregate equation based on a partial adjustment specification. They find that adding only two higher moments to a standard partial adjustment specification improves the R-bar squared from 0.647 to 0.793.[16] Second, CEH characterize and quantify the time-varying responsiveness of aggregate employment to aggregate shocks that emerges in a model with micro nonlinearities. Based on Equation 1, it is easy to show that the marginal responsiveness to an aggregate shock will, in general, be given by:

Figure 2

Relationship Between Employment Change and Employment Deviation



Black line is average adjustment ($A(x,t)$). Blue line is average density ($f(x,t)$).
SOURCE: Caballero, Engel, and Haltiwanger (1996).

(3) $$\textit{Marginal Responsiveness} = \int A(x,t)[1+\alpha(x,t)]\, f(x,t)dx\ ,$$

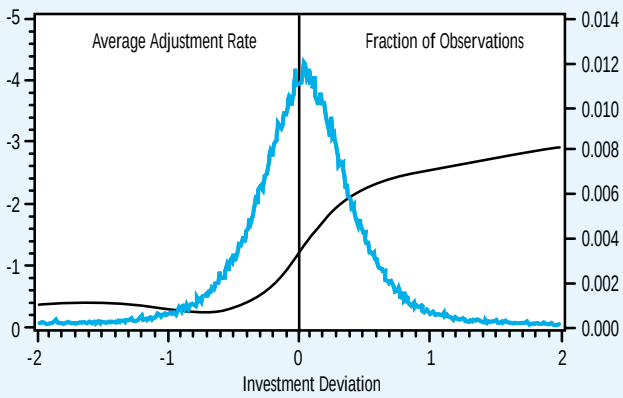
where $a(x,t)$ is the elasticity of the adjustment rate at time t, with respect to x. Standard linear models involve the first term on the right side of this equation (although without x as an argument) but only nonlinear models include the second term, which involves a weighted average of elasticities evaluated at different values of x. With estimates of $A(x,t)$ and $f(x,t)$, this marginal responsiveness can be estimated. CEH (1997) find that the marginal responsiveness for employment varies as much as 70 percent over time. Furthermore, they find that the impact of the time-varying marginal response is especially large in recessions: The decline in the 1974-75 recession was 59 percent larger than it

[15] The adjustment rate function depicted corresponds to a cubic spline fit over a fine grid. CEH (1997) characterize the adjustment-rate function in each quarter (and the corresponding cross-sectional distribution) and find that the adjustment-rate function is relatively stable over time so that most fluctuations in aggregate employment are accounted for by fluctuations in the cross-sectional distribution.

[16] To capture potential asymmetries between positive and negative adjustment at the micro level, the two moments added in CEH (1997) are the second moment of x, conditional on x being positive, and the second moment of x, conditional on x being negative.

Figure 3

Relationship Between Investment and Investment Deviation



Black line is average adjustment ($A(x,t)$). Blue line is average density ($f(x,t)$).
SOURCE: Caballero, Engel, and Haltiwanger (1995).

would have been in the absence of nonlinear adjustment.

Investment Dynamics

Nonlinearities in the adjustment dynamics of capital, driven by irreversibilities and related nonconvexities in the adjustment costs of capital, have analogous implications for aggregate investment dynamics. Several recent studies of establishment-level investment dynamics provide support for the view that micro investment dynamics exhibit lumpy adjustment. Two recent papers characterize plant-level investment as being dominated by large, scale-investment episodes—denoted investment spikes. Doms and Dunne (1994) find that, during a 17-year horizon, the largest annual change at an individual plant accounts for approximately 25 percent of cumulative investment over this period for the plant. Following on this work, Cooper, Haltiwanger, and Power (1995) find that the probability of an investment spike is increasing in the time since the previous spike, lending additional support to the view of a microeconomic environment with nonconvexities in the adjustment technology. Using the analogue of Equation 1 but with x now measured as the deviation between desired and actual capital, Caballero, Engel, and Haltiwanger (1995) (hereafter CEH, 1995) characterize the relationship between plant-level investment dynamics and aggregate investment.

Studies of establishment-level investment dynamics must confront the difficult measurement issues in generating estimates of real investment flows and capital stocks. Individual establishments purchase new and used capital and sell and retire capital. Through 1988, the LRD includes information on new expenditures, used expenditures, and retirements (including sales of assets). These series are exploited in CEH (1995) using an appropriately modified perpetual inventory method. The plant-level investment rate that CEH calculate in each period is based on the estimated difference between real expenditures and real retirements for the period, divided by the estimated beginning-of-period real capital stock.

This approach also requires measuring desired capital at the plant level. The specification in CEH (1995) assumes that desired capital is proportional to frictionless optimal capital.[17] The latter is a simpler construct and can be derived from the standard neoclassical expression. This yields a specification in which the deviation between desired and actual capital is a function of the output-capital ratio for the plant, as well as of the cost of capital.

The average adjustment-rate function $A(x,t)$ and the average cross-sectional distribution, estimated on the basis of this specification using annual LRD data for the period 1972-88, are depicted in Figure 3.[18] For plants with positive excess capital, the left arm of the adjustment-rate function (to the left of zero) is quite flat and close to zero, which is consistent with irreversibilities in investment. In contrast, the right arm of the adjustment-rate function is highly nonlinear. Plants with large shortages of capital adjust proportionally more than plants with small shortages of capital.

As with employment dynamics, the nonlinear adjustment-rate function yields time-varying elasticities of aggregate invest-

[17] A plant-specific constant is used to capture the distinction between desired capital (the level of capital that would be chosen if adjustment costs were momentarily removed) and frictionless capital (the level of capital consistent with a simple neoclassical model in the absence of frictions).

[18] A balanced panel of large, continuing plants (about 7,000) is used in this analysis.

ment with respect to aggregate shocks. For investment, the marginal responsiveness generated by the analogue of Equation 2 exhibits a procyclical pattern and varies by as much as 70 percent. The time-varying elasticities suggest a possible explanation for the often puzzling response of aggregate investment to cost of capital and other shocks. The basic idea is that the difficulties the empirical aggregate investment literature has had in quantifying the relationship between aggregate investment and the cost of capital are a result of the failure to incorporate the time-varying responsiveness generated by the interaction of nonlinear micro adjustment and heterogeneity.

Productivity Dynamics

The heterogeneous fortunes of individual producers raises a variety of questions about the underlying forces generating the heterogeneity. Several strands of the theoretical literature on firm dynamics and heterogeneity are helpful in providing guidance and in turn suggest that the ongoing process of reallocation is likely to be important for understanding both micro and aggregate productivity growth.

Models of selection (as in Jovanovic, 1982, and Ericson and Pakes, 1994) suggest that individual producers face uncertainty about either their initial conditions that determine the level of productivity at a particular production site or about the productivity consequences of retooling and reorganizing their production processes. The learning process implies dynamic selection as producers learn about the success of their start-ups and their attempts at retooling. Vintage models of technological change as in Solow (1960); Cooley, Greenwood, and Yorukoglu (1994); and Cooper, Haltiwanger, and Power (1995) stress the idea that new technology is often embodied in new capital. In this environment, the presence of idiosyncratic shocks, along with fixed costs of adjusting capital, help explain productivity differences across production sites. Related models by Caballero and Hammour (1994), Mortensen and Pissarides (1994), and Campbell (1995) stress the idea that new technology is embodied in the creation of new plants, which in turn displace outmoded, older plants. Sunk costs limit entry so that new, high-productivity plants coexist with lower productivity, older plants. Another related but distinct class of models characterizes the adoption of new technologies via the endogenous innovation and imitation process.[19] In these latter models, producers must incur costs (both direct and indirect) to acquire and implement new technology. In addition, individual producers are subject to idiosyncratic shocks (e.g., demand, cost, and productivity). The presence of these adoption costs, along with idiosyncratic shocks, implies variation in technology adoption and productivity across producers.

The picture that emerges from this growing literature is one in which technological change is a noisy, complex process with considerable experimentation (in terms of entry and retooling) and failure (in terms of contraction and exit) playing integral roles. The evidence on large-scale, within-sector job reallocation provides indirect support for this perspective. More direct empirical analysis of the implications of the pace of reallocation and restructuring for productivity dynamics has been recently provided by Baily, Hulten, and Campbell (1992); Olley and Pakes (1992); and Bartelsman and Dhrymes (1994) for a selected number of industries using the LRD. These studies find that the reallocation of output from less-productive to more-productive plants within industries plays an important role in the observed patterns of industry-level total factor productivity (TFP) growth. In the balance of this subsection, some of the analysis of Baily, Hulten, and Campbell (1992) is extended to all manufacturing industries. In addition, the decomposition I use here provides a more comprehensive and detailed examination of the contribution of within-plant, between-plant and net-entry changes to industry-level TFP.

Following Baily, Hulten, and Camp-

[19] See, for example, Jovanovic and MacDonald (1994) and Andolfatto and MacDonald (1993).

Table 3

Decomposition of Total Factor Productivity Growth*

Census Period	Total	Within	Between	Covariance	Net Entry
1977-87	10.73	5.84	-1.11	4.03	1.97
1977-82	2.43	-0.30	-1.26	3.52	0.43
1982-87	8.26	4.76	-1.39	3.92	0.96

*Selected periods, percentage increases during the period.

SOURCE: Tabulations from LRD, based on decomposition in Equation 7.

bell, plant-level productivity for plant i in period t is measured as:

$$(4) \quad \ln TFP_{it} = \ln Q_{it} - \alpha_K \ln K_{it} - \alpha_L \ln L_{it} - \alpha_M \ln M_{it},$$

where Q_{it} is real gross output at plant i in period t and K_{it}, L_{it}, and M_{it} are capital, labor and intermediate inputs, respectively. The capital input includes structures and equipment treated separately, and the intermediate inputs includes material inputs and energy purchases treated separately. The index of industry-level productivity in year t used by Baily, Hulten, and Campbell is given by:

$$(5) \quad \ln TFP_t = \sum_i \theta_{it} \ln TFP_{it} ,$$

where θ_{it} it is the share of gross output for plant i in period t for the industry. The measure of industry productivity growth between periods $t-k$ and t is then measured as:

$$(6) \quad \Delta \ln TFP_t = \ln TFP_t - \ln TFP_{t-k} ,$$

In what follows, the plant- and industry-level measures for productivity are constructed from the LRD for the census years 1977, 1982, and 1987. The details of the measurement of gross output, inputs, and factor elasticities (measured via cost shares) are discussed in the Appendix but essentially follow that of Baily, Hulten, and Campbell (1992). The standard difficult measurement issues in constructing measures of real output and inputs (in particular, for example, the construction of the real capital stock) that are always confronted in measuring TFP are amplified in this type of microeconomic analysis. In addition, the plant-level data are incomplete on some important dimensions. For example, other than some limited information collected on contract workers, the ASM and thus the LRD do not include information on purchased services.

The decomposition considered here for a given industry is as follows:[20]

$$(7) \quad \Delta \ln TFP_t = \sum_{continuers} \theta_{it-k} \Delta \ln TFP_{it} + \sum_{continuers} (\ln TFP_{it-k} - \ln TFP_{t-k}) \Delta \theta_{it} + \sum_{continuers} \Delta \ln TFP_{it} \Delta \theta_{it} + \sum_{entering\ plants} \theta_{it} (\ln TFP_{it} - \ln TFP_{t-k}) - \sum_{exiting\ plants} \theta_{it-1} (\ln TFP_{it-k} - \ln TFP_{t-k}) .$$

The first term in this decomposition represents a within plant component based on plant-level changes, weighted by initial output shares in the industry. The second term represents a between-plant component that reflects changing output shares, weighted by the deviation of initial plant productivity from the initial industry index. The third term represents a covariance term. The last two terms represent the contribution of entering and exiting plants, respectively.

In this decomposition, the between-plant term and the entry and exit terms involve deviations of plant-level productivity from the initial industry index. For a continuing plant, this implies that an increase in its output share contributes positively to the between-plant component only if the plant has higher productivity than average initial productivity for the industry. Similarly, an exiting plant contributes positively only if the plant exhibits productivity lower than the initial average, and an entering plant contributes posi-

[20] This decomposition differs from that in Baily, Hulten, and Campbell (1992) in a few subtle, but important, respects. The differences and consequences are discussed in detail in the Appendix.

tively only if the plant has higher productivity than the initial average.

This decomposition is undertaken at the four-digit industry level for 1977-87, 1977-82, and 1982-87, using plant-level data from the CM. Weighted averages of the industry-level decompositions are reported in Table 3. Following Baily, Hulten, and Campbell (1992), the weights used to aggregate across industries are the industry share of nominal gross output, averaged over the beginning and ending years of the period over which the change is measured.[21] Several interesting patterns emerge. First, the within-plant component is quite important but is far from telling the entire story. For example, for the period 1977-87, the within-plant component accounts for about half of the average industry change. The between-plant component is uniformly negative but relatively small, while the covariance term is uniformly positive and large. For the 1977-87 period, the covariance term accounts for about 40 percent of the average industry change. It is clear from this result that the shift in output towards plants that are also increasing productivity is a major factor in accounting for the average industry change. Net entry plays an important supporting role as well. For the 1977-87 period, net entry accounts for about 18 percent of the average industry change. Taken together, these results imply that about half of the increase in productivity for the average industry is accounted for by composition effects involving the reallocation of output across production sites.

The contribution of the various components varies over time and apparently throughout the cycle. The period 1977-82 exhibits very modest average productivity growth. Interestingly, both the within-plant and the between-plant components are negative for this period. The modest increase in the overall average during this five-year horizon is accounted for by a relatively large and positive covariance component, as well as a positive net-entry component that offsets the contribution of the within- and between-plant components. In contrast, the period 1982-87 exhibits robust average productivity growth, with large positive contributions from the within-, covariance, and net-entry components.

Table 4

Output Shares and Relative Productivity

	Output Shares		Relative Productivity Indexes			
Census Period	Exiting Plants *(t-k)*	Entering Plants *(t)*	Exiting Plants *(t-k)*	Entering Plants *(t)*	Contiuing Plants *(t-k)*	Contiuing Plants *(t)*
1977-87	20.1	15.9	0.99	1.10	1.00	1.11
1977-82	7.7	7.7	1.01	1.01	1.02	1.03
1982-87	12.2	8.3	0.99	1.09	1.01	1.11

SOURCE: Tabulations from LRD. TFP indexes are relative to calculated TFP index in 1977 for all plants, based on Equation 5.

Table 4 provides information about some of the underlying determinants of the decomposition by reporting output shares of entering and exiting plants and the weighted average of productivity levels for continuing, entering and exiting plants.[22] The reported productivity indexes are relative to the weighted average for all plants in 1977. Entering plants tend to be smaller than exiting plants, as reflected in the generally smaller output shares of entrants (relative to exiting plants). Entering plants in period t tend to have higher productivity than the level of productivity in period $t-k$ for exiting and continuing plants, but entrants exhibit slightly lower productivity than continuing plants in period t. Exiting plants from period $t-k$ tend to have lower productivity than continuing plants in period $t-k$. Thus, entering plants tend to displace less-productive exiting plants, but enter with about the same productivity as continuing plants.

These results are very much in the spirit of the findings reported by Baily, Hulten, and Campbell (1992); Olley and Pakes (1992); and Bartelsman and Dhrymes (1994). The message that emerges is that the reallocation of output across plants plays a very important role in accounting for aggregate measures of productivity growth (specifically, here,

[21] It is important to emphasize that the decomposition is for industry productivity growth and the weighted average across industries does not capture the reallocation of output between industries. Thus, the weighted industry averages are not directly comparable to overall changes in productivity for total manufacturing. In spite of this disclaimer, a comparison with overall changes in productivity growth in total manufacturing, based on the Bartelsman and Gray (1995) published ASM data, yields quite similar overall patterns.

[22] As in Table 3, the industry-level productivity indexes are weighted by the average of the industry share in nominal gross output in the beginning and ending periods.

through the reallocation of output towards establishments with rising productivity). Furthermore, the relative contribution of the reallocation varies through time. Putting these two results together suggests that documenting and understanding the process of reallocation is important for understanding the determinants and the fluctuations in aggregate productivity growth.

Putting the Pieces Together

Recent evidence from studies using establishment-level data make a prima facie case that aggregate fluctuations in key aggregates like employment, investment, and productivity can only be understood by building from micro evidence. Large and time-varying rates of within-industry job reallocation indicate that micro heterogeneity is pervasive and plays an important role in characterizing underlying driving forces and in characterizing fluctuations. The bursts of permanent job destruction at the onset of recessions are closely linked to the observed persistence in unemployment rates during the cycle. Nonlinear micro adjustment of labor and capital inputs, in combination with this heterogeneity, imply time-varying elasticities with respect to aggregate shocks. The underlying reallocation also plays a fundamental role in characterizing aggregate productivity dynamics. The reallocation of output towards establishments with rising productivity and the supporting contribution of more-productive entering plants displacing less-productive exiting plants account for about half of the growth in average industry productivity in U.S. manufacturing during the 1980s. In addition, the contribution of the process of reallocation to productivity growth varies over time, suggesting that understanding fluctuations in aggregate productivity growth requires tracking the contribution of reallocation.

Many of the findings thus far should, of course, be viewed as only suggestive because they primarily reflect the behavior in U.S. manufacturing and are plagued by their own measurement and conceptual problems (this is particularly true for the analysis of productivity). However, progress on these dimensions can only be made by developing and improving the requisite longitudinal micro databases—the topic to which we now turn.

DATA COLLECTION, PROCESSING, AND MEASUREMENT

Building the microeconomic databases required to pursue a longitudinal microeconomic approach to measurement and analysis of aggregate fluctuations is a formidable challenge. My discussion in this section is cast in terms of the database collection, processing, and measurement issues that must be confronted to pursue this approach, given the current practices of the U.S. statistical agencies. In addition, the discussion highlights economists' limited understanding of a variety of key conceptual and measurement issues that serve as additional obstacles to this approach.

The ideal, of course, is to build a comprehensive longitudinal establishment database that would be based on a representative *longitudinally matched* sample of establishments, including a representative sample of births and deaths. This data set would have unique, time-invariant establishment identifiers, enabling linking of establishments over time, as well as indicators-of-ownership structure so that establishments of multi-unit companies could be linked together. Variables in the data set would include detailed information about location, establishment age, industry, output, capital, labor, and intermediate inputs (including energy and purchased services), as well as detailed information about wages and prices. Measurement of output would include a detailed breakdown of the products and/or services provided by this establishment. Such a data set could be used for micro studies of establishment and firm behavior, as well as for characterizing the connection between micro dynamics and aggregate fluctuations along the lines discussed earlier in the sec-

[23] I have neglected many of the applications of longitudinal business data to a variety of other topics and questions. See McGuckin (1995) for an overview of the type of analysis that has and can be done with longitudinal micro data on the business population. Bartelsman (1995) provides a related discussion that also considers related findings for the Netherlands.

tion entitled, "Micro Heterogeneity and Aggregate Fluctuations: A Brief Review of Recent Evidence."[23]

Is it possible under current practices to build anything remotely resembling this wishful fiction? Building this type of database requires a comprehensive, integrated approach to the collection of statistics on the U.S. business population.[24] As I indicated at the beginning of this article, various federal agencies conduct different surveys and censuses to collect current information on the U.S. business population. The various pieces of information are matched at an aggregate (e.g., industry) level.

It is instructive in this regard to consider briefly the various data sources drawn on to produce published industry real output and productivity (i.e., labor and total factor) indices. Although it is well beyond the scope of this article to provide a complete characterization of the data sources and procedures the statistical agencies use to measure macro aggregates,[25] even a crude characterization reveals the nature of the process and the limitations in terms of building micro databases.

One key ingredient in building published aggregate statistics are the economic censuses taken every five years by the Bureau of the Census. The economic censuses collect data from the universe of all establishments, covering the manufacturing, wholesale trade, retail trade, service, construction, agriculture, transportation, and mineral industries. The primary data collected are payroll and nominal gross revenue. For many sectors, information on employment, intermediate inputs, and asset expenditures are also collected, although the level of detail varies dramatically across sectors. This information from the economic censuses on gross revenue, intermediate input expenses, and asset expenditures are vital for the Bureau of Economic Analysis (BEA) to build its industry input-output tables. These infrequently revised tables (the latest input-output table now available is from 1987) are used by BEA, along with annual industry-level tabulations of gross output, to construct measures of sectorial value-added. The annual industry-level tabulations of gross output are based on the annual surveys conducted by the Census Bureau, which collects information on gross revenue, as well as information from other sources for sectors with inadequate annual surveys. Constructing sectorial real gross output measures, as well as real value-added, requires the generation of both output and intermediate input deflators. The Bureau of Labor Statistics (BLS) collects the output deflators separately. The intermediate input deflators are derived from the output deflators and the input-output matrixes. The sectorial real value-added measures that emerge are the core of the product side of the gross domestic product (GDP) accounts and in turn are used for a variety of other purposes, including generating labor and total factor productivity statistics (e.g., those produced by the BLS).[26]

In terms of the measurement of other inputs for officially published productivity statistics, the employment, hours, and payroll information is based on the BLS establishment survey (the 790 data), which in turn is benchmarked to the ES-202 data, based on state unemployment insurance administrative data. Since hours data in the BLS 790 data are restricted to nonsupervisory workers, hours data are further supplemented by information from the Current Population Survey (CPS).

Investment expenditures by industry are generated by using the shipments, imports, and exports of capital goods from the annual surveys conducted by the Census Bureau and other sources, along with the input-output tables. Construction of capital stocks are generated using perpetual inventory methods that in turn requires investment deflators and depreciation rates. Because deflators and depreciation rates vary widely across asset types, the measurement of real expenditures and stocks by industry requires detailed information on asset expenditures by industry. Historically, no data have been collected on detailed asset by industry (rather, at best, information distinguishing between

[24] This call for a comprehensive, integrated approach to the collection of business population statistics is not new. (See, for example, Griliches, 1994; the Bonnen report, 1981; and Triplett, 1991, for related discussion and additional references).

[25] See, for example, Carson (1987), for an excellent overview of the data and sources used to generate the National Income and Product Accounts.

[26] BLS uses different interpolation and extrapolation procedures between economic censuses so that BLS measures of sectorial productivity differ from those generated from the BEA procedures.

structures and equipment has been collected). The BEA capital-flows tables used to allocate detailed asset types across industries are based on auxiliary information. For example, in describing the release of a new Capital Flows Table (CFT) in 1985, Silverstein (1985) notes that "most distributions were made in proportion to some indicator, such as employment, assumed to be correlated with the use of the commodity." Like the rest of the input-output tables, the construction of the CFT is an arduous, time-consuming process. For example, Silverstein (1985) reports that the CFT released in 1985 was based on the 1977 input-output accounts (from the 1977 Economic Censuses). The typical indicator used to allocate assets to industries in the CFT released in 1985 is the occupational mix of employment by industry, based on the occupation-by-industry report from the 1970 Census of Population, extrapolated to 1977. Thus, real capital expenditures and stocks by industry after 1985 are based in part on information collected many years earlier and on assumptions of some fixed relationship between asset use by industry and the occupational mix of employment by industry.[27]

This depiction is incomplete. Nevertheless, it causes one to imagine that aggregate statistics emerge from some great black cauldron, mixed together with data from an alphabet soup of surveys.[28] A host of well-known problems arise with this merging of diverse sources of data (collected by a variety of different agencies) having different sample frames and consequently different properties. The level of detail and disaggregation varies substantially across sectors so that strong assumptions are necessary to match the data across sources. In a similar manner, the information collected is in many cases incomplete. Heroic assumptions underlying imputation procedures, along with matching data from different sources, are therefore necessary to construct the measure of interest (e.g., the measurement of real capital stocks and expenditures, using the CFT). Another problem is that the benchmark detailed estimates are available only at five-year intervals and often with a substantial lag so that the higher frequency (e.g., annual, quarterly, and monthly) data involve substantial interpolation and extrapolation.

A related problem in matching the data across sources is that some of the underlying data are from sample frames at the establishment level while others are at a company or employer taxpayer-identification level. This distinction matters in terms of industrial classification of the relevant outputs and inputs. Many of the largest companies have multiple establishments, operating in a variety of industries (crossing two-digit and one-digit boundaries). The sectorial classification of activity will differ in important ways, depending on how the activities of such large companies are allocated across industries. Establishment-based surveys tend to classify all of the activity in a given establishment in a single detailed (e.g., four-digit) industry while company-based surveys classify all activity for an entire company in a single, broader (e.g., two- or three-digit) industry based on the major activity of the company.[29] This implies that, even under a common industrial classification system, company-based and establishment-based surveys yield different pictures of the industrial composition of activity. Matching information across such sources at the industry level has obvious problems.

The objective here is not simply to reiterate the "well-known" problems associated with building existing aggregate statistics from myriad sources, but to consider the formidable challenge of what would be required to take heterogeneity and aggregation issues seriously in the measurement and analysis of aggregate fluctuations.[30] The discussion in the remainder of this section accordingly proceeds as follows. First, I review some problems with the manufacturing sector (having arguably the best longitudinal micro data) since this discussion is instructive for the more general problems that must be confronted in building a comprehensive longitudinal database. Second, I discuss the problems with matching data from myriad sources,

[27] This combination of imputation, interpolation, and extrapolation procedures raise questions about the use of these capital stocks by industry for measurement and research purposes. For example, these procedures raise particularly serious questions about using these capital stocks by industry to investigate hypotheses regarding issues such as capital-skill or technology-skill complementarity.

[28] One source of incompleteness in this discussion is the neglect of higher frequency sources of data for monthly and quarterly aggregate statistics.

[29] Some company-based surveys (e.g., the new Annual Capital Expenditures Survey) ask companies to provide information about their activities in separate two-digit or three-digit industries.

[30] "Well-known" is in quotes because, although many of these issues are well-known in the statistical community, they are not generally well-known by research economists using the data.

both cross sectionally and longitudinally at the *micro level*. Third, I discuss the conceptual challenges in building new longitud- inally based aggregate statistics. Finally, I conclude with some brief remarks that contrast the concerns raised here about measurement with the many other vital measurement issues we confront in analyzing aggregate fluctuations.

Problems With the Data on Businesses

The sector with arguably the best annual data collected in a manner suitable for longitudinally based analysis is manufacturing. Detailed data come from the ASM and the CM. Not only do the ASM and CM contain a wealth of information about individual establishments, the five-year panel rotation of the ASM and the comprehensive CM provide a means of linking the data longitudinally. As highlighted by the discussion of the studies in the above section entitled, "Micro Heterogeneity and Aggregate Fluctuations: A Brief Review of Decent Evidence," the longitudinally based data that have resulted (i.e., the LRD) offer the opportunity to study the dynamics of employment, wages, investment, and productivity.[31] However, even here, there are substantial limitations that in many respects are becoming more severe with time. Oddly enough, some of the growing limitations of the ASM and CM are being generated by well-intentioned efforts to improve the overall quality of economic statistics, along with concerns of reducing the reporting burden on companies. Discussing these limitations is illustrative of the problems that must be overcome in building longitudinal establishment databases.

A number of key variables have been eliminated from the ASM through the years. In 1980, the series on quarterly hours for production workers was dropped. After 1988, much of the detail on capital stocks and capital expenditures was dropped. Before 1988, the ASM included beginning- and end-of-period book values for equipment and structures, new expenditures on equipment and structures, used expenditures, and retirements. Since 1988, only new expenditures on equipment and structures have been included.

The motivation for these deletions is typically based on the argument that the series in question duplicates information that some other survey (perhaps by some other statistical agency) collects and is eliminated to reduce costs and reporting burdens. For example, the hours data used in the National Income and Product Accounts and BLS productivity tabulations are derived from the BLS 790 and the CPS. Since ASM hours data were not a vital part of creating published aggregates, they were deemed expendable. Likewise, detailed ASM data on capital stocks and expenditures were deemed expendable, given the manner in which the BEA capital stocks and expenditures are constructed and given the recently initiated Annual Capital Expenditures Survey (ACES).[32]

These deletions, however, severely limit the ASM and thus the LRD as a source of longitudinal establishment data for the 1990s and beyond. In terms of the empirical studies discussed in the above section on micro heterogeneity and aggregate fluctuations, these changes severely limit the ability to conduct future analogous types of analyses. For example, the analysis on nonlinear adjustment of employment is based on a sample terminated in 1980, given the elimination of the quarterly hours series. Likewise, the studies of plant-level investment dynamics described in the section on micro heterogeneity and aggregate fluctuations used samples terminating in 1988, given the elimination of the detail on expenditures, retirements, and book values. In general, investment and productivity studies using the LRD were severely hampered after 1988, given the elimination of the detail on capital stocks and expenditures.

Although the information contained in the ASM is deteriorating over time, it is important to emphasize in this context that the ASM still contains a vast amount

[31] Furthermore, the manufacturing sector comes relatively close at times to the "plug & play" approach advocated in the section entitled "Can the Existing Microeconomic Data Be Linked Across Sources and Time" in that many of the special surveys can be linked at the micro level. For example, detailed data on the type of technology adopted at plants have been collected in the Survey of Manufacturing Technology (SMT). A variety of recent studies (see, e.g., Doms, Dunne, and Troske, 1997) have matched the micro data on technology use to the CM micro data.

[32] ACES has some quite attractive features in that it covers all sectors and periodically will provide detailed asset expenditures information to provide needed information on the mix of assets being accumulated.

of information relative to the data collected for many nonmanufacturing sectors (e.g., services). The annual surveys conducted by the Bureau of the Census for nonmanufacturing sectors often are limited to collecting information on gross revenue, employment, and payroll. Some surveys for individual sectors contain limited information on expenses but even then the expenses are often combined under one item (e.g., total operating expenses). The sampling unit is typically not only an establishment but rather a mixture of establishments, companies, and business units identified by taxpayer employer identification numbers (EINs). Note that companies may use multiple EINs. Furthermore, the annual surveys outside of manufacturing do not have the five-year panel-rotation feature of the ASM that permits longitudinal analysis.

Can the Micro Data Be Linked?

Given the manner in which business population data are currently collected in the United States, one obvious question is, can the various micro data sets at the statistical agencies be appropriately linked at the micro level? In principle, there is no reason why all the ingredients for longitudinal establishment-based statistics and analyses of employment, investment, or productivity need to be collected in a single survey or by a single statistical agency. However, as emphasized above, the problem is that the collection of information from the U.S. business population is not based on a comprehensive, integrated approach. Two related issues must be considered in this context: First, can the micro data be matched cross-sectionally across sources? Second, can the micro data be matched longitudinally? Several examples illustrate the problem of linking the data on both of these dimensions at the micro level.

As a first example, consider the possibility of using ACES as the source of micro data on investment and using the Census Bureau's annual surveys of various sectors as the source of information for shipments or revenue (e.g., to measure gross output). For concreteness, it is illustrative to consider specifically the problems of matching up the micro data from ACES and the ASM. An immediate problem is that ACES is a company-based survey, while the ASM is an establishment-based survey. Although the ASM includes company identifiers, it is a sample of establishments and thus not all establishments of multi-unit establishment companies are included. This implies that one could not successfully aggregate the ASM to a company level and match to ACES. Another problem is the nature of the panel rotation. The ASM is drawn every five years, with a representative sample of births added each year to the ongoing five-year panels. A new ACES sample is drawn every year. Although large certainty establishments (ASM) and certainty companies (ACES) are included in every survey, small business units (either companies or establishments) cannot be linked across panel rotations. Because a new ACES sample is drawn every year, it cannot be used to generate a representative matched panel of companies across years, much less used to match longitudinally to the LRD or ASM.

For another example, consider the BLS 790 establishment survey. It contains monthly information on hours, employment, and payroll on an establishment basis but huge obstacles arise that would have to be confronted to link it up to the various micro data sets that contain information on shipments, other inputs, and capital expenditures at the Census Bureau. One serious obstacle is that current confidentiality laws and restrictions severely limit statistical agencies' data sharing at the micro level. The confidentiality protections are essential since it is imperative to protect the confidentiality of respondents data from households and companies. Each of the statistical agencies is committed to providing such protection as reflected in the current set of similar restrictions that each agency has in place. What is needed is for micro data at all of the federal statistical agencies to be protected under a common set of restric-

[33] Some recent proposed legislation (H.R. 3924) would put all statistical agencies under the same confidentiality restrictions and thus permit data sharing for statistical purposes across the statistical agencies.

tions so that data can be shared across the statistical agencies.[33] Even after overcoming these monumental legal problems, the linkage would face serious obstacles. The BLS 790 data is an establishment survey but is not based on a representative sample. Furthermore, the BLS 790 survey is voluntary, so many longitudinal holes exist in the micro data. BLS has a variety of procedures to overcome these limitations in building aggregates from the 790 survey but these limitations restrict the usefulness of the 790 as a micro database.[34]

What needs to be done to develop a more comprehensive, integrated approach to the collection of statistics by the U.S. business population? It is beyond the scope of this article to explore the statistical agencies' organizational changes needed to achieve a comprehensive, integrated approach to the collection of business population statistics. One avenue for achieving such objectives is to create a central statistical agency for the United States. It is worth noting that both Canada and France have such central statistical agencies and have surpassed the United States in terms of the development of longitudinal business databases. Indeed, in France, a longitudinal database with matched employers and employees has been developed that yields a host of additional possibilities beyond those discussed above (see, e.g., Kramarz, 1994). Even if creating a central statistical agency is not feasible, the creation of a virtual central agency through close coordination and data sharing is essential to collect business population statistics in a comprehensive and integrated fashion. This call for coordination across statistical agencies is far from new, but one argument made by Triplett (1991) and McGuckin (1995) is worth repeating in this context. Both these authors argue forcefully that the coordination across the statistical agencies is only possible through maintaining and building the capability for research and analysis at the statistical agencies. Their basic argument is that research capability at the statistical agencies is essential for providing the necessary links between the producers of the data and the users of the data. The voice of new ideas and research in the program planning process is crucial in the current context. My main argument here is that new research with longitudinal business population data points towards a need for rethinking the manner in which we collect and process data for producing aggregate statistics. This rethinking is only possible if this new research has a voice at the statistical agencies, with influence on the operational collection and processing of statistics.

Beyond the organizational changes that may be required, one key is to use a common master business establishment list and to follow a "plug & play" approach to the collection of business population statistics. If all business population statistical surveys are establishment based and drawn from a common frame that maintains consistent establishment, company, and industry identifiers, then the data can be matched at the micro level. The most desirable approach is to keep all surveys at the establishment level since mixing data from establishment and company surveys generates the type of problem discussed above in matching ACES to ASM data.[35] Another essential aspect to a successful "plug & play" approach to building longitudinal business data is to ensure that the rotation of establishments in an individual survey over time is such that it permits creating a representative sample of longitudinally matched plants (along with a representative sample of establishment births and deaths). The frequency of panel rotation of the establishments in surveys is also important to consider in this context because it will affect the frequency at which longitudinal analysis can be conducted. To the extent that the data are collected by different surveys for the same sector that will be matched cross-sectionally, appropriate coordination of the panel rotation is required.

In spite of the somewhat pessimistic tone I have taken above, the United States is not that far away from achieving some aspects of this comprehensive, integrated approach for U.S. business population sta-

[34] BLS uses a ratio-of-change estimation procedure to overcome these problems in generating aggregates from the survey. Furthermore, the BLS benchmarks some of the tabulations (e.g., employment) from the 790 to its master business establishment data file (the ES-202 data discussed later in the article).

[35] It may be, however, that in some industries it is very difficult to collect information at the establishment level. Furthermore, some data items are inherently company-level variables (e.g., financial assets and liabilities) or are difficult to collect at the establishment level (e.g., exports). These difficulties do not negate the importance of measuring certain types of behavior at the establishment level (e.g., employment growth, investment, and productivity growth) but rather highlight the need to link relevant establishment-level behavior with relevant company-level variables (e.g., financial variables and exports).

[36] One question is why both agencies are maintaining business-establishment lists. As discussed above, legal data-sharing restrictions lurk at the root of this redundancy.

tistics. The Census Bureau and the BLS now both maintain master business establishment lists.[36] The Standard Statistical Establishment List (SSEL) maintained by the Bureau of the Census is a master business list based on administrative data and survey sources that cover all employers with at least one employee. The business unit in the SSEL is typically an establishment, and the file contains establishment, enterprise, location, and industry identifiers, as well as basic information on payroll and first quarter employment from Internal Revenue Service files. The SSEL is the frame from which the Census Bureau conducts the economic censuses, as well as its various annual surveys. Furthermore, it is through the SSEL, the annual Company Organization Survey, and the economic censuses that the Census Bureau tries to maintain accurate establishment and firm identifiers. The BLS maintains a similar administrative record file (the ES-202 data), based on Unemployment Insur- ance files. The ES-202 data are the frame underlying the BLS surveys of establishments. Furthermore, the BLS conducts a multi-site workplace survey to track the ownership linkages between establishments.

The SSEL and the ES-202 can potentially serve as the core on which to build comprehensive, longitudinal establishment databases. Indeed, several ongoing projects use both of these data sets on a limited basis. For example, plans are under way to use the ES-202 data to produce annual and quarterly gross job-creation and job-destruction statistics by industry, state, size class, and wage class for the entire U.S. economy. This is possible with the ES-202 data without linking it to any other information because the ES-202 data already contain employment data.[37] Thus, the administrative record databases currently used for sample frames should be viewed as primary data sources for longitudinally based statistics.

Using either the SSEL or ES-202 as a longitudinal frame or database requires substantial effort. Both are based on tax records and the core identifiers in the files are thus tax identification numbers (EINs) and/or Unemployment Insurance (UI) account numbers. A variety of ownership and organizational structure changes yield changes in EIN and UI account numbers. Furthermore, multi-unit firms may maintain one or several tax identification numbers and again may change these in response to a variety of circumstances. Longitudinal linkage problems in using these files are substantial. As an example, in constructing the LRD during the 1972-88 period, staff and researchers at the Center for Economic Studies at the Bureau of the Census detected more than 5,000 longitudinal linkage problems in the ASM even after the Census Bureau processing procedures had assigned permanent plant identifiers (PPNs) that were supposed to be permanently affixed to a particular location. Pursuing these longitudinal linkage problems outside of manufacturing is a monumental task in light of the more than 7 million establishments with more than one employee.[38] Nevertheless, recent efforts at both the Census Bureau and BLS indicate that these longitudinal linkage problems can be overcome.[39]

To summarize briefly, collecting business population data in a comprehensive and integrated manner is essential for building the type of longitudinal business databases necessary for understanding the underlying driving forces for key macro aggregates like employment, investment, and productivity growth. The path towards a more comprehensive, integrated approach involves the following steps.

- Permit data sharing across the statistical agencies and thus create a common master business establishment list.
- Exploit the information in the administrative data (underlying the business establishment lists) to the fullest extent to build longitudinally based statistics.
- Base censuses and draw samples for all surveys of businesses from the master business list so that micro data and

[37] Similarly, the SSEL has already been used to generate statistics on the changes in the distribution of employment growth by company and establishment size in a contract with the Small Business Administration (see, e.g., Trager and Moore, 1995, for more discussion). Furthermore, linking the micro records in the SSEL, economic censuses, and annual surveys would permit analysis of the joint distribution of employment growth and labor-productivity growth (measured using gross output measures) at the establishment level.

[38] Furthermore, greater conceptual problems arise outside of manufacturing in specifying what one means by an ongoing establishment. In principle, the Census Bureau assigns a PPN that reflects ongoing activity at some fixed, physical location. In the retail trade and service sectors, it may be inappropriate over the course of time to link a particular retail location that houses a variety of different retailers selling a wide variety of products and services.

[39] See, for example, Spletzer (1995) and Trager and Moore (1995).

associated aggregate statistics can be linked.

- Introduce appropriate panel rotation in the samples of businesses in the surveys to permit construction of longitudinal statistics from survey data.

Although these steps would be extremely useful for many statistical and research purposes (including those advocated here), even larger payoffs await a more fundamental change in the manner in which business statistics are collected. The myriad surveys and censuses of businesses conducted by the different statis- tical agencies impose a heavy burden on respondents and yield a host of problems in linking the data at the micro and the aggregate level for the users of the statis- tics. Finding some effective means of streamlining this process so that all the data from an individual business for a given period is collected at one time would yield tremendous benefits to both respondents and data users.

Parsimonious Ways to Summarize the Micro Hetergeneity

In addition to the problems of building the requisite longitudinal business databases, this approach to aggregate analysis has a variety of other measurement and conceptual problems that need to be confronted. One general problem is that parsimonious ways of summarizing and aggregating the relevant information have yet to be developed. Even if all the logistical obstacles discussed above are overcome, it is unlikely that longitudinal business databases created at the statistical agencies will ever be widely accessible to the research and policymaking communities. Confidentiality restrictions inherently imply limited access to the micro data with associated monitoring to prevent inadvertent disclosure.[40] Furthermore, even with the increasing speed and disk capacity of computers, the underlying micro databases are enormous.

The question then is whether new aggregate measures of the distribution of the micro changes and activity can be developed that would prove useful for analysis of aggregate fluctuations. Gross job-creation and job-destruction rates are an example of new aggregates that can be generated from longitudinal micro data. Furthermore, one could easily imagine that other basic, descriptive decompositions like those used in Equation 7 to decompose industry productivity growth could prove quite useful. Knowing the relative contribution of within-establishment, between-establishment, covariance, and net-entry components of aggregate measures of productivity growth would undoubtedly shed considerable light on the determinants of the aggregates.

Because a basic insight of this approach is that higher moments matter for aggregate fluctuations, it would also appear at first glance that the studies on nonlinear micro adjustment and aggregate fluctuations yield promising suggestions for aggregates that could be created. The problem here is that the higher moments that matter involve the difference between desired and actual variables. For example, the measurement of the desired capital stock is model dependent with a number of reasonable alternative specifications. This model dependence is apt to be a generic issue in considering the link between micro and macro behavior. However, even without consensus on specification, the analysis in the section on micro heterogeneity and aggregate fluctuations provides some suggestions of measures that might be useful. For example, the analysis of the aggregate implications of nonlinear micro adjustment for employment described in the same section depends critically on measuring the distribution of establishment deviations between actual and "normal" hours per worker at the establishment. The related analysis of nonlinear micro adjustment and aggregate investment dynamics depends critically on the distribution of establishment output-capital ratios. Both of these cases yield relatively simple and intuitive suggestions of potentially relevant measures of the distributions of activity at the establishment level. The challenge is,

[40] The opening of a Census Research Data Center (RDC) in Boston and at Carnegie-Mellon University are one important way these limitations on data access can be overcome. The Census RDC's permit researchers to work with the micro data without coming to Census-headquarters in Washington which maintaining strict monitoring of the research output to prevent disclosure of the confidential micro data. A Census Bureau employee is detailed to each RDC to provide the necessary liaison between the researchers and the Census Bureau.

in general, to find creative ways to summarize the relevant microeconomic distributions of activity and change in a manner that can be widely used (i.e., not idiosyncratically linked to a narrowly specified model or functional form).

CONCLUSION

Let me close by briefly comparing and contrasting these concerns about heterogeneity and aggregation issues with the host of other measurement problems confronting our measurement of real activity. The conceptual issues (e.g., how to measure output in certain service industries), as well as the associated limited data collected in the service sector, are first-order problems. Dealing with quality change and new goods and services are perennial problems in the measurement of output, inputs, and prices. Given limited budgets for statistical agencies, changes in data collection and processing procedures that address these issues deserve high priority. However, my view is that implementing the data and processing procedures required for addressing these heterogeneity and aggregation issues should be on the list of priorities as well. Addressing these heterogeneity and aggregation issues is in many ways complementary with addressing the other measurement difficulties that we face. After all, trying to measure investment, real output, and productivity growth at the establishment level forces consideration of the conceptual issues and the limited data availability problems at their most basic and primitive level. Furthermore, the longitudinal microeconomic approach to the production of aggregate statistics advocated in this article implies a comprehensive, integrated approach to the collection and processing of statistics that has many benefits and is long overdue.

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Appendix

MEASURING PLANT-LEVEL TOTAL FACTOR PRODUCTIVITY AND DECOMPOSING THE AGGREGATE

Measurement Issues

The Census of Manufactures (CM) plant-level data used in the analysis in the section on productivity dynamics contains information on shipments, inventories, book values of equipment and structures, employment of production and nonproduction workers, total hours of production workers, and cost of materials and energy usage. For the most part (exceptions noted below), the measurement methodology used in the section on productivity dynamics follows closely that of Baily, Hulten, and Campbell (1992). Real gross output is measured as shipments adjusted for inventories, deflated by the four-digit output deflator for the industry in which the plant is classified. All output and materials deflators used are from the four-digit Bartelsman and Gray (1995) data. Labor input is measured by total hours for production workers, multiplied by the ratio of total payroll for all workers plus payments for contract work to payroll for production workers. This latter multiplication factor acts as a means for accounting for both hours of nonproduction and contract workers. Materials input is measured as the cost of materials deflated by the Gray-Bartelsman materials deflator. Capital stocks for equipment and structures are measured from the book values deflated by capital stock deflators (where the latter is measured as the ratio of the current dollar book value to the constant dollar value for the two-digit industry). Energy input is measured as the cost of energy usage, deflated by the Gray-Bartelsman energy-price deflator. The factor elasticities are measured as the industry average cost shares, averaged over the beginning and ending year of the period of growth. Industry cost shares are generated by combining industry-level data from the Gray-Bartelsman data with the Bureau of Labor Statistics (BLS) capital rental prices.

The CM does not include data on purchased services (other than that measured through contract work). Baily, Hulten, and Campbell used a crude estimate of purchased services based on the two-digit ratio of purchased services-to-materials usage available from the Bureau of Labor Statistics KLEMS data (where KLEMS refers to capital, labor, energy, materials and service inputs). Baily, Hulten and Campbell applied the two-digit ratio from the aggregate KLEMS data to the plant level data on materials. Because this is at best a crude adjustment that will not provide much help in decomposing productivity growth *within four-digit* industries, this adjustment was not incorporated in the analysis of the section on micro heterogeneity and aggregate fluctuations. Furthermore, a comparison of the results in Baily, Hulten, and Campbell with those generated here yields quite similar results for the overlap industries (they considered 23 industries) when I used their exact decomposition methodology.

The data used are from the mail universe of the CM for 1977, 1982, and 1987. In the CM, very small plants (typically fewer than five employees) are excluded from the mail universe and denoted administrative record cases. Payroll and employment information on such very small establishments are available from administrative records (i.e., the Standard Statistical Establishment List) but the remainder of their data are imputed. Such administrative record cases are excluded from the analysis in the section on productivity dynamics. In addition to the usual problems in using book-value data, for plants that were not in the Annual Survey of Manufactures (about 50,000-70,000 plants) but in the mail universe of the CM, book-value data are imputed in years other than 1987. Baily, Hulten, and Campbell investigated this issue and found little sensitivity on this dimension. This partly reflects the

relatively small capital cost shares in total factor costs when materials are included.

As a further cross-check on sensitivity to measurement issues, the analysis in the section on productivity dynamics was also conducted for labor productivity, using both gross output and value-added meas- ures of labor productivity. Besides the independent interest in labor productivity, the measurement of labor productivity (particularly on a gross output basis) is less fraught with measurement problems. Interestingly, quite similar results are generated when using output weights as the relevant shares in the decomposition in Equation 7 but now with plant-level productivity measured in terms of labor productivity. An employment-weighted decomposition of labor productivity yields roughly similar results; however, the within-plant and net-entry components play a more substantial role. Further exploration of these differences is beyond the scope of this article but interesting to note, given currently available data collection and processing procedures. That is, analysis for sectors other than manufactur-ing along the lines conducted in the section on productivity dynamics will, given the scant data collected on inputs for most sectors, need to be based on a decomposition of labor productivity measured on a gross output-per-worker basis.

DECOMPOSITION ISSUES

Although the measure of plant-level and aggregate industry-level total factor productivity follows that of Baily, Hulten, and Campbell very closely, the decomposition in 7 differs from that in Baily, Hulten, and Campbell in two important respects. The Baily, Hulten, and Campbell decomposition involved the three following terms:

- A within-plant component (they denote this term as fixed shares) that is identical to the within-plant component in Equation 7;
- A between-plant component (denoted as share effect) measured as the sum of the changes in the output shares for each continuing plant weighted by *ending* level of plant-level productivity;
- A net-entry component measured as the output-weighted average productivity of entrants less the output-weighted average productivity of exiting plants.

Thus, one difference is that by using ending-level plant-level productivity in their "share effect," their share effect captures both the between-plant and the covariance term in the decomposition in Equation 7. Second, the between- and net-entry terms in Baily, Hulten, and Campbell do not involve deviations of the relevant plant-level productivity from the initial average level of productivity in the industry. A consequence of this formula- tion is that even if all plants have the same productivity in period $t-k$ and t, the Baily, Hulten, and Campbell decomposition yields a nonzero between-plant term and an offsetting nonzero net-entry term if the share of output due to entering plants is different than the share of output due to exiting plants. Because the size of exiting plants is typically larger than entering plants, in practice this yields a bias towards a positive between-plant term and a negative net-entry term. This partly explains why Baily, Hulten, and Campbell find that the contribution of net entry is very small and sometimes negative.

On a more general methodological note, this discussion highlights the subtle but important differences in between and within decompositions in a balanced panel versus an unbalanced panel. For balanced panels, it is unnecessary to deviate the relevant term (e.g., initial plant-level productivity) in the between component from the initial overall average because the sum of the changes in shares is zero. One thus obtains identical results with and without deviating from means. This property does not hold for unbalanced panels necessitating a refinement of the standard between and within decomposition.