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External Economies at the Firm Level: Evidence from Swedish Manufacturing

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Abstract

Using the method of Caballero and Lyons (1990, 1992), I examine detailed Swedish manufacturing firm-level data on output and factor inputs from 1979 through 1994. Panel regressions show that an increase in aggregate output and inputs appears to raise individual firms' production beyond private marginal returns, a result consistent with external economies. However, while considering potential specification difficulties, this paper shows that a model in which random shifts in technology drive the business cycle statistically outperforms the Caballero-Lyons model. This finding suggests that high-frequency random shifts in technology are more important for movements in firms' productivity than are external economies.

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1. Introduction

A wide range of beneficial spillovers that increase the productivity of individual firms have been considered in the theoretical literature to explain long-term economic growth.[1] The models have the property that although each firm faces diminishing returns to the reproducible factors, the global economy may exhibit increasing returns to scale. Less attention, however, has been devoted to the empirical relevance of these models. Exceptions are Benhabib and Jovanovic (1991) who found no support for the claim that capital-related spillovers are present in cross-country and U.S. data, and Mankiw, Romer, and Weil (1992) who showed that a human capital augmented Solow (1956) growth model can yield commendable predictions without invoking constant returns to capital.

These empirical findings hence do not confirm the assumption of large spillover effects associated with aggregate capital accumulation. In contrast, evidence on productive spillover effects from R&D have been provided by Griliches and Lichtenberg (1984) and Jaffe (1986). Moreover, using a production function framework, Caballero and Lyons (1990) found evidence in four European countries on positive spillover effects from aggregate manufacturing production. Support for production externalities in U.S. manufacturing industries was found in Caballero and Lyons (1992). However, when using the Caballero-Lyons methodology, Basu and Fernald (1995) found no evidence on gross output externalities in U.S. manufacturing. Basu and Fernald provided one explanation to the different results on externalities: the use of value-added data for output in the Caballero-Lyons approach may lead to spurious findings of beneficial external effects due to misspecification. The reason, they argued, is that value-added output data possible fail to account properly for intermediate inputs, and hence these intermediate inputs may show up as false externalities. Yet, Oulton (1996) nevertheless

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[1] Important theoretical contributions include Arrow (1962), Romer (1986), Lucas (1988), Barro (1990), Jones and Manuelli (1990), Rebelo (1991), and Grossman and Helpman (1991). External economies have been used also in the theory of international trade (see Ethier (1982) and Helpman (1984)), and in the literature on business cycle models (see Baxter and King (1991), Benhabib and Farmer (1994), and Farmer and Guo (1994)).

found support for external economies in U.K. manufacturing industries using both gross output and value-added output data, suggesting that value-added measurement difficulties are not the only explanation to the obtained differences in results.[2]

The present work is related to the empirical literature on procyclical productivity.[3] It draws on the work of Caballero-Lyons, and tries primarily to determine the extent of external economies at the level of individual firms in Swedish manufacturing. An essential difference between this study and the studies referenced above is that they used data from industry levels, while here I use firm-level micro data. The analysis is based on a new and, in this context, unusually large data set including information on output and factor inputs for more than 8,000 Swedish manufacturing firms from 1979 through 1994. The principal contribution is to use this important panel data set to address the question whether the expansion of aggregate manufacturing output and inputs contributes significantly to the productivity of individual firms.

In the first part of the empirical analysis, I find that individual firms' productivity is positively associated with aggregate manufacturing activity: a 1.0 percent increase in aggregate value-added output appears to add around 0.3 percent on a period-by-period basis to each firm's output, holding firm-level inputs constant. This result is consistent with an economy characterized by substantial high-frequency external effects originating from aggregate activity. One possible interpretation of this finding is that aggregate production approximates the current level of productive knowledge in the economy, i.e., learning by doing. Increasing global returns to scale may then arise because ideas of how to produce more efficiently are non-rival, at least to some extent, implying that useful productive information diffuses across the manufacturing firms. Caballero and Lyons (1992) also suggested that aggregate activity may influence the firms' productivity by affecting the matching process between agents in the economy, a so-called 'thick market' effect. Given that transaction costs between agents are sufficiently large and inversely related to the business cycle, production costs decrease

[2] Oulton, however, found that short-run variations in firms' productivity growth appear to be caused by economy-wide technological change.

[3] For a recent study on cyclical productivity, see for example Basu (1996).

in business cycle upturns and increase in downturns. Productivity then becomes procyclical.

The size of the externality effect is, according to the empirical estimates in this study, surprisingly large given the interpretation that this effect represents either productive knowledge spillovers or ‘thick markets’. While the estimated externality coefficient typically is around 0.3 when aggregate activity is measured by aggregate value-added output, some estimates suggest that it should be even larger. This paper argues that although one could certainly tell reasonable stories for why this externality coefficient should be significantly larger than zero, given the maintained interpretation, estimates around (or above) 0.3 are not very plausible. It certainly is, as earlier pointed out by Basu and Fernald (1995), rather difficult to identify such large beneficial effects in actual manufacturing firms. As a consequence, the empirical analysis is expanded to consider some data difficulties and possible specification errors (such as cyclical measurement errors in inputs from unobserved factor utilization rates, and problems associated with omitted variables) that can potentially explain the obtained results without resorting to external economies.[4] The analysis suggests that unmeasured fluctuations in labor effort and capital utilization rates are not the single cause of the findings of apparent external economies in Swedish manufacturing. This conclusion is reached both when the basic Caballero-Lyons model is expanded to consider labor effort, and when a deep recession period is excluded from the data. Another possibility is that aggregate activity approximates unmeasured technological change in the form of continuing changes in the number of specialized intermediate inputs. If these inputs are highly productive and available throughout the economy, then aggregate activity may appear to increase firms’ output beyond private marginal returns.[5] This measurement difficulty is however not investigated further in this study because the data lack

[4] A number of theoretical and methodological problems typically arise when econometric production functions are implemented at the level of individual firms. For an overview of these issues, see for example Griliches and Mairesse (1995).

[5] Aggregate output can alternatively be interpreted as an approximating variable for the average *degree* of specialization of the individual firm’s production factors. According to Romer (1986), for example, changes in the level of technology is determined endogenously by the firms, and technological progress avoids the tendency for diminishing returns to scale.

information on intermediate inputs. Furthermore, since knowledge typically diffuses gradually across firms, productive spillovers are rather likely to be operative over longer periods of time. As a result, the empirical analysis also considers delayed spillover effects from aggregate activity. The empirical results suggest that delayed external effects are not present.

The analysis then considers an alternative empirical specification in which individual firms' production is subject to exogenous economy-wide productivity shocks. The reason for applying this model is that aggregate activity is identical across each single manufacturing firm in every time period, and hence aggregate activity may serve only as an approximating variable for economy-wide random shifts in technology. Hence, movements in the firms' productivity can be positively associated with changes in aggregate output and inputs because global activity simply approximates exogenous shifts in technology. The empirical analysis shows that a model in which period-by-period exogenous shifts in technology drive the business cycle statistically outperforms the Caballero-Lyons model. This finding strongly suggests that the estimates presented in this paper are more likely to represent exogenous fluctuations in technology that are identical across all manufacturing firms in every time period than high-frequency external economies. Short-run movements in the firms' productivity are then driven exclusively by economy-wide technical change rather than beneficial spillover effects associated with aggregate activity. This result provides strong micro data support for the stochastic real business cycle models in the tradition of Kydland and Prescott (1982). In these models, temporary shifts in the level of technology are the principal source of macroeconomic fluctuations.

The rest of the paper proceeds as follows: Section 2 outlines the analytical framework of Caballero-Lyons. Section 3 provides a data description, and section 4 presents some empirical results. Section 5 then investigates the robustness of these empirical findings with respect to the interpretation that innovations in technology are more important for fluctuations in individual firms' productivity than are external economies. Concluding remarks finally close the paper in section 6.

2. Analytical Framework

Special features of the Caballero-Lyons model include both external economies and technological progress.[6] Caballero and Lyons (1989) postulated an industry-specific value added production function and derived an expression for the change in output as a function of the change in industry-level inputs, aggregate manufacturing activity, and technology. Thus, their model compares movements in output with movements in inputs and, accordingly, relates to the growth accounting literature originating from Solow (1957). Following this approach at a lower level of aggregation, consider now a general production function for a single firm:

$$Y = F(K, L, E, V), \tag{2.1}$$

where Y is total value-added (gross output net of intermediate inputs), K and L are measures of capital and labor inputs, E is an external economy index, and V is the level of technology. This production function is homogenous of degree γ in the conventional inputs capital and labor, of degree one in E, and of degree one in V.[7] Logarithmic differences of (2.1) together with the homogeneity conditions yields

$$dy = \gamma dk \left(\frac{F_L L}{Y} \right) (dl - dk) + de + dv, \tag{2.2}$$

where dy, dk, dl, de, and dv are the growth rates of Y, K, L, E, and V. The marginal product of labor is denoted by F_L. Equation (2.2) can be further simplified by making the assumptions that firms have some monopoly power in output markets (but not in the market for factor inputs) and that the behavior of firms can be approximated by a sequence of static problems.[8] For a single firm (now indexed by i) these assumptions result in

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[6] The model is highly influenced by Hall (1988), who however considered only internal returns to scale.

[7] Note that because E and V are indices of external effects and productivity growth, the homogeneity assumptions can be viewed as simple normalizations.

[8] For details, see Caballero and Lyons (1989).

$$dy_{it} = \gamma_{it} dx_{it} + de_{it} + dv_{it}, \tag{2.3}$$

where $dx_{it} = \alpha_{it} dl_{it} + (1-\alpha_{it}) dk_{it}$ is a weighted index of input growth, and α_{it} is the share of firm *i*'s labor in total factor costs. The variables and parameters are written with a time subscript *t* to emphasize that they can change over time. Hence, the growth rate of individual firms' output can be expressed as the product of the elasticity of output with respect to capital and labor inputs (γ_{it}) and the activity level at the firm level (dx_{it}), plus the change in the external effect index (de_{it}) and technology (dv_{it}).

Assume now that the change in productivity evolves over time according to $dv_{it} = dv + \varepsilon_{1it}$. Hence, productivity growth equals the sum of a constant component dv and a pure random term ε_{1it}.[9] Further, let the change in the external economy index be determined by $de_{it} = \beta_{it} de_t + \varepsilon_{2it}$. The external effect at the firm level is thus generated by an aggregate variable de_t (possibly a vector) and a disturbance term ε_{2it}. Substitution of the expressions for de_{it} and dv_{it} into (2.3) yields

$$dy_{it} = \gamma_{it} dx_{it} + \beta_{it} de_t + \varepsilon_{it}, \tag{2.4}$$

where $\varepsilon_{it} = \varepsilon_{1it} + \varepsilon_{2it}$.[10] This is the equation that formed the basis for the estimates reported in the studies by Caballero and Lyons. It enables an investigation of spillover effects operating at various levels of aggregation. In the present study, I investigate whether an increase in one-digit manufacturing activity, as measured by the growth of aggregate value-added output and aggregate weighted inputs, raise the productivity of individual firms. A significant estimate of β thus represents evidence of an external-

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[9] Fluctuations in output are here seen as arising solely from supply disturbances. For a discussion of both demand- and supply-determined macroeconomic fluctuations, see Blanchard (1989) and Blanchard and Quah (1989).

[10] A constant has been suppressed in (2.4).

to-firm effect associated with aggregate manufacturing activity. Returns to scale that are internal to the firms are captured by estimates of γ.[11]

A variety of production functions can be represented by equation (2.4). For example, in Romer (1986) the external effect variable de_t corresponds to aggregate physical capital, and in Lucas (1988) and Sala-i-Martin (1996) de_t corresponds to aggregate human capital. Moreover, Barro (1990) assumed that external effects originate from aggregate public spending.

3. Data Description

Most empirical studies of internal and external economies in manufacturing industries have used aggregate data. The present study, in contrast, is based on input and output measures from the firm level. In general, disaggregate data provide more information than data from aggregate levels because more observations are used and no aggregation bias is present. In addition, applying production models to micro data is generally intuitively appealing since firm-level data typically are consistent with the underlying firm-level theories. However, due to prevalent disaggregate measurement difficulties, aggregate data may sometimes nonetheless be more reliable.

The current data set represents a subsample of the Corporate Statistics (CoSta) data base, which is provided by Statistics Sweden (SCB). It includes unpublished nominal time-series book-value records of value-added, capital and labor inputs, and factor costs for Swedish manufacturing firms for the years 1979-1994.[12] The present sample covers the complete population of manufacturing firms with 20 employees or more, and a stratified sampling procedure has been used for the remaining smaller firms.

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[11] Note that since random growth of productivity (ε_{1it}) may be correlated with capital and labor inputs, estimation of (2.4) generally requires instrumental variable techniques. This estimation difficulty will be further considered in the empirical section.

[12] The CoSta data base has been used previously by Forsling (1996, 1998), who investigated the degree of utilization of tax allowances in Swedish corporate firms.

Since new firms continuously enter the manufacturing sector, the panel data set is characterized by several missing observations in the beginning of the period. Analogously, since there are firms leaving the manufacturing sector, there are missing values also at the end of the period. The data set hence is unbalanced in the sense that each year's input-output information possible pertains to different firms. While a total of 11,377 manufacturing firms initially were included in the panel data, only input and output growth rates for 8,581 firms were, due to the unbalanced nature of the data, observed. In order to eliminate spurious effects due to outliers and changes in variable definitions, input and output observations characterized by very high growth rates (i.e., positive growth rates of inputs and output beyond 200 percent, negative growth rates of inputs less than –100 percent, and negative growth rates of output less than –200 percent) are excluded, implying that the number of firms declines to 8,441 and that the number of total observations declines from 49,580 to 47,898.[13] Thus, around 2 percent of the firms and 3 percent of the total observations are excluded.

Capital is measured by book values of the stocks of machinery, buildings, and land, and labor by the average number of employees per year.[14] Value-added output and capital are deflated by a two-digit producer price index.[15] In order to derive an indicator of the firm-level input activity dx_{it}, capital and labor are, according to equation (2.3), weighted by their shares in total factor costs. Total labor compensation (i.e., total wage expenses, health insurance, and pensions) is used for the labor cost. Following Hall and Jorgenson (1967), the user cost of each of the three assets (machinery, buildings, and land) is computed according to:

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[13] I have experimented with some less restrictive benchmark values for these outliers. This did not qualitatively affect any results.

[14] The average number of employees per year is typically computed at the level of individual firms as the 'volume of labor' during a year translated into the number of annual full-time employees. It follows from this definition that, although significant intra- as well as inter-firm variation may be present, this measure is, on average, rather likely to reflect the true (effective) labor input.

[15] The deflator is obtained from the Statistical Yearbook of Sweden. Take notice that the current data do not include price information for individual firms, implying that firm-specific deflators cannot be used. Abbot (1991) found that estimates of production function parameters using firm-specific deflators may yield different results than estimates using industry-wide deflators. For more details on this issue, see

$$r_j = (\rho + \delta_j)\frac{1 - c_j - \tau d_j}{1 - \tau}, \; j = 1, 2, 3, \tag{3.1}$$

where ρ is the real rate of return required on capital, δ_j is the economic rate of annual depreciation of asset j, c_j is the proportion of the original investment cost of the jth asset that is subsidized, τ is the corporate tax rate, and d_j is the asset-specific proportion of the original investment cost that can be deducted from income for depreciation reasons. Following Caballero and Lyons (1992), I assume that machinery depreciates geometrically with 12.7 percent per year (i.e., $\delta = 0.127$), and that the required rate of return on capital ρ equals the real dividend yield on long-term government bonds. The corporate tax rate τ is the same as in Forsling (1996). Since 30 percent of the current book value of machinery is deductible, the present value of depreciation allowances for an investment in machinery is $d = 0.3/(0.3 + i)$, where i is a constant nominal interest rate. Depreciation allowances for buildings and land are typically very low, and they have varied over time and across industries. Since the present data lack information on these allowances they are neglected. Neither buildings nor land are assumed to depriciate.[16]

The required payment for the jth asset equals $r_j \pi_j K_j$, where $\pi_j K_j$ is the current value of the stock of this particular asset. The total cost of employing capital, broadly measured as the sum of machinery, buildings, and land, then equals the sum of the required payment for each of the three assets.

Grilishes and Klette (1992), who identified some difficulties of interpretation of the production function parameters when aggregate deflators are used.

[16] Note that due to various measurement difficulties, estimates of r are at best approximations to the true cost of capital. However, since capital generally is less cyclical than labor, it should be 'safer' to underestimate r than the opposite. The reason is that spurious cyclical errors in equation (2.4) are less likely to show up when labor's share is large. I have experimented with slightly different measures of r without qualitatively affecting any results.

Table 3.1 reports some descriptive statistics of firm-level growth rates of value added (dy_i), capital (dk_i), labor (dl_i), weighted inputs (dx_i), and labor's share in total factor costs (α_i). The aggregate analogues are marked by subscript *a*. Here, dx_a is defined as a weighted average of the percentage change in aggregate capital and labor, i.e., $dx_a \equiv \alpha_a dl_a + (1-\alpha_a)dk_a$, where α_a is the average of labor's share across all firms. A closer look at the data (not reported in table) reveals that approximately 50 percent of the firms are observed 4 years or less. According to table 3.1, labor's share in total factor costs is surprisingly high. In the U.S., a more typical range for labor's share in total factor costs would probably be around 60-75 percent. One tentative explanation for why labor's share in total costs is high in Sweden during the relevant sample period is that Swedish firms, from 1980 through 1993, were allowed to reduce their current tax payments by subtracting up to 20 percent of total labor costs from their taxable incomes. Although other complementary tax rules may, at the same time, have subsidized capital investments, this very large subsidize directed towards labor may have resulted in larger numbers of employees as well as higher labor costs.[17]

Apart from potential random measurement errors, one limitation of the available data is that differences in the quality of production factors are not completely accounted for. In particular, although capital inputs are measured in three different ways, the measure of labor input does not consider the distribution of competence levels among the employees. In Basu and Fernald (1995), however, quality-adjusted workforce and capital data provided similar results as non-adjusted data, suggesting that the induced error of not taking into account input qualities might not be crucial. Another limitation is the lack of information on the utilization rates of factor inputs. Labor input is, however, as pointed out in footnote 14, computed as the 'volume of labor' translated into its full-time labor equivalent. Hence, given that the volume of labor adequately reflects variations in labor effort at the level of individual firms, this measure reflect the true (effective) labor input. However, since the measure of capital inputs does not take into account variations in capital utilization rates, these difficulties in the

[17] According to Forsling (1998), this additional tax rule was introduced mainly to subsidize firms' in the service sector. This rule implied that all firms could, by using certain profit equalization funds, postpone tax payments corresponding to 20 percent of total wage expenses.

measurement of factor inputs should not be ignored. The theoretical ideal should, of course, be input measures adjusted for quality differences as well as utilization rates.[18] Furthermore, because the data include only a fraction of the firms with less than 20 employees, the aggregate activity measures that are used in this study largely mimic the dynamics of the larger firms. As a consequence, aggregate activity may potentially affect larger firms more than the smaller firms. A final limitation is that the panel data do not include information on intermediate inputs, such as energy, materials, and business services. This lack of information precludes a gross output formulation of the Caballero-Lyons model.

4. Empirical Analysis

The work reported in this section focuses on estimation of the benchmark equation (2.4) with aggregate manufacturing output and inputs as the source of possible beneficial spillovers that may increase the productivity of individual firms.

Estimation of equation (2.4) raises a few econometric issues. The first concerns the nature of the panel data set and the construction of the relevant variables. The data set is unbalanced, which has some practical consequences for the estimation procedures. For example, if lagged values from the firm level are to be used somewhere in the regressions, then a number of observations (and firms) will be excluded from the data. This is unavoidable when using unbalanced data. Second, equation (2.4) allows for parameters varying over time and across firms. This general setup brings with it several estimation difficulties. For simplicity, the parameters γ and β are therefore initially constrained to be constant over time and across firms. Since all variables in (2.4) are expressed in rates of growth, unvarying firm-specific level effects are however

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[18] Many studies have identified the problems associated with measuring of factor inputs. Recent examples are Bernanke and Parkinson (1991) who considered difficulties in the measurement of labor input when analyzed procyclical labor productivity in U.S. manufacturing, and Griliches (1994) who argued that measurement difficulties may be a major cause of the slow progress in our understanding of productivity growth. Moreover, due to difficulties in measuring input utilization rates, Benhabib and Jovanovic (1991) treated capital as well as labor as unobservable in some regressions.

implicitly controlled for. Third, since the error term ε_t in equation (2.4) is likely to be correlated with both own input activity (dx_t) and the aggregate external variable (de_t), the estimates of γ and β are possibly biased. The reason for this dependency is that the error term includes unobservable productivity shocks in firms' technology (ε_{1t}), which may affect the demand for firm-level capital and labor inputs as well as aggregate activity. For example, if the level of technology shifts upwards, then manufacturing output as well as firms' inputs probably increase; labor and capital inputs rise to exploit the extra productivity, and aggregate manufacturing output is affected directly. As a result, the estimates of γ and β possibly are upward biased. On the other hand, if factor inputs are measured with random errors, then the estimates of γ are downward biased.[19] It is not possible to determine *ex ante* the direction of this bias. The standard way of dealing with both these problems is to use an instrumental variables technique. Hall (1988), Caballero and Lyons (1992), and Basu and Fernald (1995) used as instruments the political party of the president, military expenditures, and the price of oil. Caballero and Lyons (1990), however, argued that the bias in ordinary least squares (OLS) of equation (2.4) is likely to be small. Therefore, since valid instruments were difficult to find, they also included OLS estimates. In what follows, I report both OLS and instrumental variable estimates.

Table 4.1 presents OLS estimates with industry-specific dummies included to adjust the intercept for industry differences.[20] The externality variable de_t is measured by the growth of aggregate manufacturing value-added dy_a, aggregate weighted inputs dx_a, aggregate capital dk_a, and aggregate labor dl_a. The table has six columns. The first gives the row number, and the second the externality variable that is used for de_t in equation (2.4). The third and fourth columns provide the estimates of γ and β, and the fifth column gives the adjusted R^2 statistics. The final column reports the number of observations.

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[19] See, for example, Darnell (1996).

The first row of table 4.1 shows the OLS estimate of the internal returns to scale parameter γ when the externality term e_t is excluded from equation (2.4). The remaining rows show the estimation results when an externality term is included. All estimates suggest that the degree of internal returns to scale is significantly lower than 1.0. This result seems rather implausible since under monopolistic competition (and small profits) the output price then, on average, is less than the marginal cost at the level of the individual producer.[21] In Caballero and Lyons (1990), the estimates of γ also implied decreasing returns to scale in the manufacturing sector of Germany, France, U.K., and Belgium, but they did not pay much attention to this result since their major focus was on the externality parameter.[22] In a comment on their paper, however, Cohen (1990) questioned these low estimates, and Basu and Fernald (1995) argued that a spurious finding of external economies, due to improper use of value-added data, may cause a downward biased estimate of γ. Another explanation to the low returns to scale is, as already mentioned, that random measurement errors in the firm-level input growth rates are present.

Turning now to β, the parameter of primary interest, table 4.1 shows that a 1.0 percent increase in aggregate manufacturing output and inputs appears to raise output at the level of individual firms with around 0.16-0.53 percent, holding firm-level inputs constant. Although these estimates may appear to be surprisingly large, given that they represent either useful knowledge spillovers or 'thick market' effects, they agree well with empirical results from earlier studies. Using value-added data, Caballero and Lyons obtained estimates of β in the range 0.49-0.89 (1989), 0.3-1.4 (1990), and 0.32-0.49 (1992). Oulton found estimates in the range 0.10-0.18 (gross output data) and 0.20-0.24 (value-added data), and in Basu and Fernald (1995) value-added estimates ranged from 0.16 to 0.63, while gross output estimates were generally not significantly different from zero. Of course, one could certainly tell reasonable stories for why the

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[20] White's (1980) procedure is used in all regressions throughout this study to correct the residuals for heteroscedasticity.

[21] For details, see Basu and Fernald (1995).

[22] Their point estimates of γ ranged from 0.33 (France) to 0.82 (U.K.). Moreover, when Caballero and Lyons (1992) investigated U.S. manufacturing industries they found γ estimates between 0.75 and 1.05.

estimates of the externality coefficient should be larger than zero, given the maintained interpretation that productive ideas diffuse instantaneously across individual firms or that 'thick market' effects are present. However, are empirical estimates around 0.2-0.5 really plausible? Basu and Fernald (1995) argued that such large beneficial effects in actual manufacturing firms can hardly be identified, and this paper will argue that the obtained estimates are indeed surprisingly large. This issue is analyzed further at the end of the present section and in section 5.

Table 4.2 shows two-stage least squares (2SLS) estimates of equation (2.4). Lagged values of K, L_i, and Y_a are used as instruments.[23] Following earlier work by Caballero and Lyons, I now (for ease of presentation) consider only external economies associated with aggregate activity as measured by the growth of aggregate output and aggregate weighted inputs. Note that if there are random measurement errors in the levels of the variables, then the error term in the differentiated form may exhibit a first-order serial correlation. This observation is an argument for using instruments lagged more than one period. The second and third column of table 4.2 show the instruments that are used to predict changes in firm-level weighted inputs and aggregate manufacturing activity; the second column gives the variables and the third column the lag structure of the instruments.[24] Column five and six report the adjusted R^2 statistics for OLS regression of the firms' weighted inputs dx_i and aggregate activity de, respectively, on the instruments. The final column reports the statistics of the Sargan instrument validity test (c.f. Sargan (1958) and Hansen (1982)). The null hypothesis of the test is that the instruments are independent of the error term and that the model is well specified. To derive the Sargan statistic, the 2SLS residuals are first regressed on

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[23] The reason why lagged levels are used as instruments rather than lagged growth rates is that a larger proportion of the data set then is used. Using lagged growth rates as instruments yields similar results.

[24] The lags in the third column refer only to the instruments from the firm level (i.e., K_i and L_i). For Y_a, only the first and second lag (first six rows) and the second and third lag (last six rows) are used. The reason why the disaggregate lag structure on K_i and L_i is allowed to vary more than the aggregate lag structure on Y_a is that (i) movements in the disaggregate variable dx_i are harder to predict than movements in the aggregate variables dy_a and dx_a, and (ii) Y_a lagged more than three periods often turns out to be an invalid instrument because it correlates with the error term. This way of using different lag structures on firm-level and aggregate instruments is adopted throughout the whole analysis.

the instruments. Under the null hypothesis the adjusted R^2 from this regression times ($T^* - k$) have a $\chi^2(r)$ distribution. Here, T^* is the sample size, k is the number of parameters in equation (2.4) (including the intercept), and the degree of freedom r equals the number of instruments minus the number of endogenous variables on the right-hand side of equation (2.4) (i.e., the number of over-identifying restrictions). The last column in table 4.2 reports the probability of observing a test statistic at least as large as the obtained Sargan value, assuming that the null hypothesis of valid instruments is true.

The main conclusions from table 4.2 are as follows. First, although the point estimates of γ still appear to be too small, they are in six of the regressions not significantly different from 1.0 at the five percent level. Second, an increase in aggregate manufacturing output and weighted inputs still appears to raise firms' output beyond private returns. According to the estimates, a 1.0 percent expansion of aggregate output appears to raise individual firms' output with 0.27-0.37 percent, holding firm-level inputs constant. An increase in aggregate weighted inputs appears to raise the firms' output even more.[25] Third, the Sargan test suggests that the instruments are in general valid. Fourth, the instruments obviously are only weakly correlated with firm-level weighted inputs (see the fifth column). Nelson and Startz (1990) showed that poor instruments can lead to large small-sample biases of the instrumental variable estimates. Hence, although this problem is likely to be less pronounced here since the present data set is unusually large, one should have in mind that the estimates may suffer from bias.[26] Finally, the table shows a lack of robustness in the estimates of both γ and β. This may be due to the fact that the number of useful observations (and

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[25] Note that (cyclical) measurement errors in inputs due to differences between factors in use and factors available are probably a more serious problem than measurement errors in output. Hence, it is not very surprising that the estimates of the externality coefficient in the first six rows in table 4.2 differ from the estimates in the remaining rows.

[26] Note however that although the explanatory power of the instruments is low at the micro level, the first-stage F statistic (not reported in table) for testing the joint hypothesis that these instruments do not enter significantly in the first-stage regression is always larger than 30. Hence, the hypothesis of zero relevance of the instruments is always strongly rejected. According to Staiger and Stock (1997), F-

firms) declines as the number of instruments increases. The change in the composition of firms is a result of the combination of lagged variables and unbalanced data. To modify this effect, I have transformed the data set into a balanced panel including only 425 firms observed over the whole period 1980-1994. Since firms with less than 20 employees are only randomly sampled (they are hence less likely to be observed over the whole period) the balanced panel is dominated by larger firms. The OLS estimates of the balanced panel revealed no systematic change in the estimates of β, and the OLS estimates of the internal returns to scale parameter γ were slightly lower than in table 4.1. The 2SLS estimates of γ were somewhat lower than in table 4.2 while the instrumental estimates of β were slightly higher. The disperion of all estimates was however roughly unchanged.

I have also checked directly for various types of heterogeneity in firms' production behavior. I found that the estimated internal and external returns to scale parameters vary very little with the size (in terms of number of employees) of the firms. However, there are some differences between firms from distinct industries. For example, there are strong support for external economies in the wood, paper, publishing, chemical, petroleum, and primary metals industries, but no externalities are found in the food, tobacco, textile, and mineral industries.[27]

One objection, at least in principle, to the benchmark model described in equation (2.4) is that it takes time for growth-promoting spillover effects of aggregate activity to influence the productivity of individual firms. In order to allow for such delays, the production function (2.1) can be rewritten as $Y = F(K, L, E_{-s}, V)$, where t denotes time and s represents a time lag. The analogue of equation (2.4) with constrained parameters is $dy_i = \gamma dx_i + \beta de_{-s} + \varepsilon_i$. If lags are at all important, then the estimates of β should be positive for some s larger than zero. When I estimated the equation for different values of s, however, the externality coefficient β was generally

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values less than 10 are associated with estimation difficulties since they indicate that the asymptotic approximations of the distributions of instumental variables statistics are break down.

[27] See appendix B.

insignificantly different from zero or even significantly negative. Given that the interpretation of the results obtained so far is that gradual diffusion of knowledge is present, this result seems implausible. The estimates presented in tables 4.1 and 4.2 may instead represent effects that are operative over shorter time horizons, such as beneficial fluctuations-oriented ’thick market’ externalities. As already mentioned, however, the magnitude of this apparent externality effect might be too large for this interpretation to be entirely credible.

Another remark is that spillovers are likely to be larger among firms within the same industry, and hence aggregate activity measures from more disaggregate levels should yield larger estimates of β in equation (2.4). I therefore calculated output and input growth rates of both two-digit and three-digit manufacturing, and then re-estimated the regressions. There was generally not enough independent movements in the aggregate variables to get significant estimates of all coefficients simultaneously, and when I included two-digit and three-digit activity measures separately into equation (2.4), the estimates of γ and β were in general similar to the results of table 4.2.

A number of other questions can be raised about the robustness and interpretation of the results reported in this section. First, does it matter for the conclusions that firms in the Caballero-Lyons approach are assumed to behave according to static first-order conditions? Given that capital and labor cannot be adjusted without costs, these first order conditions may provide incorrect descriptions of firm behavior. Second, is equation (2.4) critically misspecified due to the use of incorrect measures of value-added data? The reason for this concern is that Basu and Fernald (1995) showed that improper measures of value-added data may cause spurious findings of external economies. Third, does aggregate manufacturing activity approximate exogenous productivity shocks that are common to all firms in every time period?

Unmeasured Factor Utilization

Input measures generally suffer from the problem of how to measure capital and labor and their utilization rates. For example, the so-called labor-hoarding hypothesis emphasizes transaction costs of adjustments in the labor force: firms may find it profitable to substitute labor utilization rates for measured labor input when the labor force cannot be modified without costs, and as a result effort levels may change over the business cycle instead of measured inputs. The same argument applies also to capital inputs which can be utilized in various degrees. The omission of factor utilization rates from weighted inputs dx_i in equation (2.4) understates the productive contribution of inputs. It follows that if factor utilization rates correlate positively with aggregate activity, then the externality finding in this section may in fact represent only procyclical measurement errors.

To see this formally, consider equation (2.3) without an external effect, and assume that the true (effective) growth rate of weighted factor inputs dx_i equals the measured growth rate plus a firm-specific variable denoting the degree of factor utilization: $dx_{it} = dx_{it}^m + f_{it}$.[28] Substituting this expressions for dx_i into equation (2.3) without an external effect yields the relation $dy_{it} = \gamma dx_{it}^m + \gamma f_{it} + dv_{it}$. Hence, if the utilization term f_i is positively related to the aggregate externality variable de, measurement errors can be misinterpreted as evidence of external economies.

One way of investigating the importance of procyclical measurement errors in factor inputs is to add an approximating variable for factor utilization rates on the right-hand side of equation (2.4). I have approximated unmeasured variations in factor utilization rates by total wage expenses per employee.[29] Estimation results of the expanded model $dy_{it} = \gamma dx_{it} + \lambda du_{it} + \beta dy_{at} + \varepsilon_{it}$, where du_{it} denotes the growth of total labor costs per employee, showed that the parameter λ is typically positive (as predicted by the labor-hoarding hypothesis). The beneficial effect on individual firms' output of aggregate

[28] This notation follows Caballero and Lyons (1992). Burnside and Eichenbaum (1996) modeled time-varying factor utilization rates in a similar way when they analyzed the propagation of business-cycle shocks.

[29] The implicit assumption here is that labor is compensated on current basis for variations in effort levels, and that labor and capital utilization rates evolve proportionally over time. In order to control for unobserved variations in factor utilization rates, Caballero and Lyons (1992) added overtime hours, average hours per worker, and the ratio of production to nonproduction workers to equation (2.4). Note

output remained, however, significant at conventional levels of significance. These estimates hence suggest that unmeasured factor utilization is not the central cause of the externality findings in the previous section.

To determine whether unobserved factor hoarding related to aggregate activity is present, one can moreover exclude periods of downturns and upturns in the business cycle.[30] The reason is that the difference between measured inputs and effective inputs should be higher during these periods, and hence when the amount of measurement errors declines (as periods of recessions and boosts are excluded) estimates of the coefficient on the external effect should be less significant. I therefore excluded the recession years 1991-1994 (the deepest recession since the 1930*s*) and re-estimated equation (2.4). The main conclusions were not affected.

Do value-added Data Introduce a False Externality?

Basu and Fernald (1995) argued that the use of value-added data in the Caballero-Lyons framework may cause spurious findings of external effects because real value-added data may fail to account correctly for the productive contribution of intermediate inputs. Real value-added should optimally be constructed by subtracting the productive contribution of energy, materials, and business services from real gross output. One problem may however arise when the contribution of the intermediate inputs is measured by factor payments: when output markets are imperfectly competitive, then marginal products of intermediate inputs exceed their prices and hence real value-added output may in fact depend directly on parts of the intermediate goods. It follows that false externalities may occur if firm-level intermediate inputs correlate positively with aggregate activity. According to Basu and Fernald, this misspecification can be largely corrected for by including intermediate input growth on the right-hand-side of

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that another interpretation of the term used here for variations in labor effort is that it approximates changes in firms’ human capital.

[30] Aggregate activity may, according to Sbordone (1996), provide useful information about unobserved factor hoarding in sectoral production. The argument is that economy-wide variables, through their information content about the future economic environment, may influence labor input decisions within individual sectors. The same reasoning can, of course, be applied to the level of individual firms.

equation (2.4). However, since the present data set lacks information on intermediate inputs, this possible misspecification cannot be investigated.[31]

5. Common Productivity Shocks

Aggregate manufacturing activity is identical for each manufacturing firm in every time period. From this it follows that the aggregate externality measures that were used in the previous section may approximate common productivity shocks. Consider now a general technology shock formulation of firm *i*'s production:

$$dy_{it} = c_1 + \gamma dx_{it} + \sum_{j=2}^{T} \theta_j D_{jt} + \varepsilon_{it}, \tag{5.1}$$

where c_1 is a constant, T is the number of time periods, and D_{jt} is a time dummy variable that equals 1 if $t = j$ and 0 otherwise. Equation (5.1) is a more general formulation of output growth than is the Caballero-Lyons approach. The Caballero-Lyons model $dy_{it} = c_2 + \gamma dx_{it} + \beta de_t + \varepsilon_{it}$, where c_2 is the previously suppressed constant term, imposes the restrictions $c_1 = c_2 + \beta de_t$ for $t = 1$ and $c_1 + \theta_t = c_2 + \beta de_t$ for $t = 2,...,T$ on the technology shock model. It is easy to show that these restrictions imply the following $T-2$ linear restrictions on the θ coefficients:

$$\theta_t - \theta_{t-1} = \left(\frac{de_t - de_{t-1}}{de_{t-1} - de_{t-2}} \right) (\theta_{t-1} - \theta_{t-2}),\ t = 3,...,T.^{32} \tag{5.2}$$

Hence, by investigating the set of $T-2$ restrictions defined by (5.2), the Caballero-Lyons model can be tested against the more general technology shock model (5.1). The

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31 It is also interesting to notice that Basu and Fernald (1997) argued that the Caballero-Lyons results of external economies may arise solely from aggregation bias. Of course, the firm-level results in the present study are not subject to this critique.

32 Subtract the (j-1)*th* constraint from the j*th* constraint to eliminate the constants c_1 and c_2, and then take ratios to eliminate β. Note that θ_1 equals zero.

degrees of freedom of the F statistic for a joint test of these constraints are $T-2$ and $T^{*}-k$, where T is the number of time periods, T^{*} is the number of total observations, and k is the number of parameters in equation (5.1) (including the intercept). Large values of F leads to rejection of the restrictions imposed by the Caballero-Lyons model on the more general technology shocks model. I calculated the F statistic when estimated equation (5.1) with OLS and 2SLS using both aggregate output growth and weighted input growth as the externality variable. The magnitudes of F always exceeded all relevant $F_{T-2,T^{*}-k}$ values. Table 5.2 shows the OLS results when both unbalanced (*U*) and balanced (*B*) data are used. To eliminate the possibility that the results are caused by the recession years 1991-1994, separate regressions are made for the subinterval 1980-1990. The last column reports the probability of observing a test statistic *F* at least as large as the obtained value, assuming that the restrictions in (5.2) hold.[33] The restrictions imposed by the Caballero-Lyons model are always strongly rejected.

Hence, taken at face value, the analysis suggests that the empirical results of section 4 can be explained in a competitive setting by exogenous economy-wide technological shocks. Movements in firms' productivity are then positively related to changes in aggregate output and input measures because aggregate activity simply approximates exogenous shifts in technology. A similar result was found by Oulton (1996). This result provides strong support for stochastic real business cycle models in the tradition of Kydland and Prescott (1982). In these models, temporary shifts in technology are the principal source of economic fluctuations.[34] Changes in the level of technology can, for

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[33] These *F* values are compared with $F_{0.05;13;\infty} \approx 1.75$, $F_{0.01;13;\infty} \approx 2.18$, $F_{0.05;9;\infty} \approx 1.88$, and $F_{0.01;9;\infty} \approx 2.41$.

[34] One could perhaps argue that the inclusion of time dummy variables in the Caballero-Lyons model eliminates most of the contribution of aggregate activity form the data. An alternative approach would obviously be to allow both for external economies and aggregate technical change. This approach would, however, suffer severely from identification difficulties since approximating variables must be used for externalities as well as technological change. It turns out that when time dummy variables are added to equation (2.4), the externality coefficient are rather sensitive to which periods that are covered by these dummy variables. This finding does not support the externality interpretation. One could, of course, also argue that if the externality interpretation cannot survive in the regressions presented in this study, despite more than 45.000 observations, then external effects are probably not very important.

example, result from new production processes, and discrete changes in certain rules and regulations that affect the incentives to adopt more (or less) advanced technologies. Macroeconomic fluctuations can also arise from random variations in government policy variables. All these changes in the level of technology is, according to the real business cycle theory, assumed to be outside the control of individual firms.

6. Concluding Remarks

To summarize, the basic empirical finding of this paper is that movements in aggregate output and aggregate weighted inputs are positively associated with the productivity of individual firms. A 1.0 percent increase in aggregate output appears to add around 0.3 percent on a period-by-period basis to each firms' output, holding firm-level inputs constant. Although this effect may seem surprisingly large, one possible interpretation of this finding is that aggregate inputs and output approximate the current level of productive knowledge in the economy (learning by doing). According to this view, spillovers of knowledge are treated as externalities because protection of proprietary information is incomplete. Productive knowledge hence is non-rival, at least to some extent, implying that useful information diffuses across all firms in the economy. An alternative interpretation, suggested by Caballero and Lyons (1992), is that aggregate activity influence the firms' productivity by affecting the matching process between agents in the economy (a so-called 'thick market' effect). If transaction costs between agents are sufficiently large and inversely related to the business cycle, then production costs might decrease in business cycle upturns and increase in downturns.

Since knowledge typically diffuses gradually across firms, productive spillovers are rather likely to be operative over longer periods of time. However, when the empirical implementation is allowed to include delayed spillover effects, the results indicate that low-frequency external effects are not present. This finding cannot easily be reconciled with the interpretation that the empirical estimates of section 4 represent productive knowledge that diffuses gradually across firms. In contrast, however, since productive effects associated with 'thick markets' are rather likely to be operative on a period-by-period basis, it seems to be a legitimite question to ask whether the empirical findings of apparent contemporary beneficial spillover effects should instead be interpreted as supportive of unmeasured variations in the transaction costs between agents. This paper argues that the obtained results support neither true knowledge spillovers nor ‘thick markets’. One reason for this view is that, according to the empirical estimates, the size of the externality effects is too large. Although the externality coefficient generally is around 0.3, some empirical estimates suggest that it should be even larger. It certainly is, as earlier pointed out by Basu and Fernald (1995), rather difficult to single out examples of such large beneficial effects in actual manufacturing firms. This paper therefore gives attention to data difficulties and possible specification errors that can explain the obtained results without resorting to external economies. In order to investigate whether the empirical findings represent unmeasured capital and labor utilization rates, the basic Caballero-Lyons model is expanded to include variations in labor effort. A deep recession period is also excluded from the data. Section 4 argues that the empirical results cannot easily be explained by unmeasured variations in factor utilization rates. An alternative interpretation of the results is that aggregate activity approximates technological change in the form of continuing variations in unmeasured specialized intermediate inputs. Given that these intermediate inputs are highly productive and ready available throughout the economy, aggregate activity may appear to increase the firms’ marginal products beyond private marginal returns. This omitted-variable difficulty is not analyzed further in the present study because the available data lack information on intermediate inputs.

Section 5 then expands the empirical analysis to consider a model driven by exogenous technology shocks in production. The reason for applying this model is that aggregate activity is identical across each single firm in every time period, and hence aggregate activity may serve as an approximating variable for random shifts in technology. Section 5 shows that the restrictions imposed by the Caballero-Lyons model on the more general technology-shock model are strongly rejected by the data. This result suggests that exogenous shifts in aggregate technology are more important for movements in firms’ productivity than are positive external effects. This analysis thus provides substantial micro data support for the simple assessment in the real business cycle models that random exogenous variations in the productivity of individual firms are the driving force of economic fluctuations.

Appendix A: Derivation of the Basic Equation

In this paper I used the following model, first laid out by Caballero and Lyons (1989). Consider a general production function $Y = F(K, L, E, V)$ for a single firm. Value-added output is denoted by *Y*, *K* and *L* are capital and labor, *E* is an index of external economies, and *V* is the level of technology. Further, let *F* be homogenous of degree γ in capital and labor, of degree one in *E*, and of degree one in *V*. Logarithmic differences of *F* yield equation (2.2):

$$dy = \gamma dk\left(\frac{F_L L}{Y}\right)(dl - dk) + de + dv, \qquad (2.2)$$

where *dy*, *dk*, *dl*, and *dv* are the growth rates of *Y*, *K*, *L*, *E*, and *V*, respectively, and F_L is the marginal product of labor. I have used the homogeneity conditions $(F_K K + F_L L)/Y = \gamma$ and $F_E E/Y = F_V V/Y = 1$ in the derivation. A simple expression for the ratio $F_L L/Y$ can then be found by assuming that firms (indexed by *i*) face the demand function $Y_i = (P_i / P)^{-\eta}(M / P)$. The price level of firm *i*'s output is denoted by P_i, P is the general price level, M is the monetary base, and η is the elasticity of demand. Caballero and Lyons then approximate firm behavior with a sequence of annual static problems and argue that violations of the static first-order conditions do not seriously affect their procedure. The firms are assumed to maximize the profit function $\pi_i = P_i Y_i - wL_i - rK_i$ with respect to labor and capital in every time period. The wage rate *w* and the capital cost *r* are taken as given by the firms. The first-order conditions are:

$$P_i \mu^{-1} F_L = w; \;\; P_i \mu^{-1} F_K = r, \qquad (a.1)$$

where $\mu = \eta/(\eta - 1)$ is the markup factor.[35] Now, let α_v denote labor's share in total value added ($\alpha_v = wL_i / P_iY_i$), and use the first relation in (a.1) to obtain $\mu\alpha_v = F_L L_i / Y_i$.[36] The product $\mu\alpha_v$ can in turn be rewritten in terms of γ and labor's share in total factor costs α_c by combining the two first-order conditions in (a.1) with the above-stated expression for γ:

$$\frac{P_iY_i}{wL_i + rK_i} = \frac{\mu}{\gamma} \Leftrightarrow \mu\alpha_v = \gamma\alpha_c, \tag{a.2}$$

where $\alpha_c \equiv wL\ /(wL\ + rK\ )$. Substitution of $\gamma\alpha_c$ for $F_L L / Y$ in (2.2) then yields the equation that is used in this study:

$$dy\ \ = \gamma\ dx\ \ + de + dv. \tag{2.3}$$

The growth rate of the firms' inputs is denoted by $dx \equiv \alpha_c dl + (1 - \alpha_c)dk$. This completes the description of the basic model.

Appendix B: Regressions Within Industries

The present study is based on input and output measures from the level of individual firms. Micro data typically provide more informative data than aggregate data. In particular, unobserved effects can easily be controlled for either by including various dummy variables or by focusing on on more homogeneous sub-samples of the original sample. In this appendix, I present some estimates from different industries. Table b.1 shows that the degree of internal and external returns to scale appears to vary between

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[35] Note that no assumption of constancy of the markup factor is required.

[36] When output and input markets are competitive, the necessary conditions for producer equilibrium are that the share of every input in the value of output equals the output elasticity with respect to that input. It follows that under constant returns to scale (the elasticities sum to one) the value of output is equal to

industries. The point estimates suggest a rather strong support for external economies in the wood, chemical/petroleum, and primary metals industries. Very low estimates of internal returns to scale are moreover found in the paper/publishing and primary metals industries.

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the total cost of the production factors, and hence the share of labor in output then equals the share of labor in total factor costs (see Jorgenson (1986)).

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Table 3.1. Summary statistics of the relevant variables during the period 1980-1994.

Variable	Mean	Median	Std. dev.	Min.	Max.
dy_i	0.026	0.008	0.276	-1.939	1.995
dk_i	0.029	-0.055	0.360	-1.000	1.998
dl_i	-0.001	0.000	0.164	-0.993	1.979
dx_i	0.007	-0.003	0.162	-0.993	1.935
α_i	0.906	0.930	0.087	0.042	1.000
dy_a	0.016	0.001	0.071	-0.052	0.256
dk_a	0.007	0.012	0.038	-0.068	0.063
dl_a	-0.020	-0.014	0.030	-0.096	0.018
dx_a	-0.017	-0.011	0.027	-0.082	0.018
α_a	0.905	0.899	0.022	0.868	0.952

Note: In order to eliminate the effects of outliers and changes in variable definitions, input and output observations characterized by very high and very low growth rates are excluded from the sample.

Table 4.1. Unbalanced panel 1980-1994: OLS results for equation (2.4).

Equation	Externality	γ	β	$\overline{R^2}$	*Obs.*
1		0.71 (0.011)		0.17	47,898
2	dy_a	0.70 (0.012)	0.36 (0.018)	0.19	47,898
3	dx_a	0.70 (0.012)	0.53 (0.047)	0.18	47,898
4	dk_a	0.71 (0.012)	0.16 (0.029)	0.18	47,898
5	dl_a	0.70 (0.012)	0.46 (0.043)	0.18	47,898

Note: Dummy variables (not reported in table) are included to adjust the intercept for industry differences. (Standard errors in parentheses.)

Table 4.2. Unbalanced panel 1980-1994: 2SLS results for equation (2.4).

Eq.	Instr.	Lags	Ext.	dx_{it}	de_t	γ	β	$\overline{R^2}$	*Obs.*	*Test*
1	K_i, L_i, Y_a	1-2	dy_a	0.03	0.43	1.05 (0.089)	0.27 (0.044)	0.17	31,060	1.00
2	K_i, L_i, Y_a	1-3	dy_a	0.04	0.39	0.91 (0.088)	0.28 (0.049)	0.20	24,493	1.00
3	K_i, L_i, Y_a	1-4	dy_a	0.04	0.39	0.83 (0.098)	0.30 (0.050)	0.21	19,413	1.00
4	K_i, L_i, Y_a	2-3	dy_a	0.03	0.33	0.83 (0.068)	0.28 (0.036)	0.21	24,493	1.00
5	K_i, L_i, Y_a	2-4	dy_a	0.03	0.41	0.80 (0.076)	0.33 (0.035)	0.21	19,413	1.00
6	K_i, L_i, Y_a	2-5	dy_a	0.03	0.43	0.79 (0.082)	0.37 (0.039)	0.22	15,381	0.82
7	K_i, L_i, Y_a	1-2	dx_a	0.03	0.55	0.72 (0.152)	0.95 (0.175)	0.20	31,060	0.91
8	K_i, L_i, Y_a	1-3	dx_a	0.04	0.58	0.63 (0.177)	0.84 (0.208)	0.20	24,493	0.99
9	K_i, L_i, Y_a	1-4	dx_a	0.04	0.54	0.69 (0.164)	0.71 (0.193)	0.20	19,413	0.63
10	K_i, L_i, Y_a	2-3	dx_a	0.03	0.57	0.31 (0.227)	0.67 (0.229)	0.15	24,493	0.00
11	K_i, L_i, Y_a	2-4	dx_a	0.03	0.56	0.55 (0.193)	0.39 (0.198)	0.19	19,413	0.00
12	K_i, L_i, Y_a	2-5	dx_a	0.03	0.64	0.43 (0.248)	0.59 (0.241)	0.18	15,381	0.00

Note: Industry dummy variables (not reported in table) are always included as both instruments and regressors. (Standard errors in parentheses.)

Table 5.2. Tests of linear restrictions imposed by the Caballero-Lyons model on the technology shocks model.

Equation	Period	Data	Obs.	Ext.	*F*	*T*-2	$T^{*}-k$.	*Test*
1	80-94	*U*	47,898	y_a	9.07	13	47,875	0.00
2	80-94	*U*	47,898	x_a	33.28	13	47,875	0.00
3	80-90	*U*	35,635	y_a	10.59	9	35,616	0.00
4	80-90	*U*	35,635	x_a	26.15	9	35,616	0.00
5	80-94	*B*	6,315	y_a	4.10	13	6,292	0.00
6	80-94	*B*	6,315	x_a	11.84	13	6,292	0.00
7	80-90	*B*	4,631	y_a	3.82	9	4,612	0.00
8	80-90	*B*	4,631	x_a	11.95	9	4,612	0.00

Note: The first four rows show the results from the unbalanced data, and the remaining four rows show the results from the balanced data.

Table b.1. Unbalanced panel 1980-1994: 2SLS results for equation (2.4) within industries.

Eq.	Industry	dx_{it}	de_t	γ	β	$\overline{R^2}$	*Obs.*	*Test*
1	Food/Tobacco	0.01	0.41	1.71 (0.291)	−0.40 (0.104)	-	2,616	1.00
2	Textile	0.05	0.37	1.01 (0.190)	0.12 (0.138)	0.2	2,145	0.22
3	Wood	0.04	0.40	0.71 (0.162)	0.70 (0.093)	0.16	4,506	1.00
4	Paper/Publishing	0.02	0.40	0.49 (0.239)	0.16 (0.077)	0.18	4,412	1.00
5	Chemicals/Petroleum	0.03	0.43	0.96 (0.249)	0.46 (0.140)	0.18	2,628	0.72
6	Minerals	0.09	0.41	0.98 (0.111)	0.36 (0.146)	0.22	1,272	1.00
7	Primary metals	0.06	0.43	0.59 (0.254)	0.65 (0.237)	0.19	748	0.47
8	Fabricated metals	0.03	0.41	1.35 (0.143)	0.20 (0.085)	0.12	12,733	0.07

Note: External effects are measured by the growth of aggregate manufacturing output. The first and second lag of firm-level capital, firm-level labor, and aggregate output are used as instruments. A constant (not reported in table) is always included as both an instrument and a regressor. (Standard errors in parentheses.)