Estimating Production Functions When Productivity Change Is Endogenous*

Marc-Andreas Muendler¶

University of California, San Diego and CESifo

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Abstract

Production function estimation with micro-data shows that a persistent unobserved variable varies within firm or plant over time but resists treatment and may cause biases. This paper presents an estimation model of the firm under endogenous productivity change. The model implies that (i) the so-far untreated effect stems from firms' planned efficiency responses to the competitive environment and that (ii) a suitable proxy to productivity is investment interacted with a sector-level competition variable. An application to Brazilian manufacturing firm data shows that this proxy and multivariate extensions yield coefficient estimates with considerably less noise in bootstraps than alternative proxies, while reducing the difference to fixed-effects estimation and remedying commonly suspected biases. Whereas productivity change is measured consistently, scale economies are not identified when productivity and price are endogenous. JEL C51, D24

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¶muendler@ucsd.edu (*www.econ.ucsd.edu/muendler*). University of California San Diego, Dept. of Economics 0508, 9500 Gilman Drive, La Jolla, CA 92093-0508, USA

Puzzles and discrepancies plague production function estimation with firm or plant data. Griliches and Mairesse (1998) conclude in a survey: "In empirical practice, the application of panel methods to micro-data produced rather unsatisfactory results: low and often insignificant capital coefficients and unreasonably low estimates of returns to scale." At times, attempts to control for attrition, simultaneity, and endogeneity problems aggravated rather than resolved these unsatisfactory findings. A prime reason appears to be that both observed variables (such as sales, capital and employment) and unobserved variables (such as firm-level productivity and individual business prospects) are highly persistent and correlated.

Most strikingly, empirical studies by Olley and Pakes (1996), Levinsohn and Petrin (2003) and others document that the fixed-effects estimator disagrees markedly with other estimators. This indicates that a persistent shock, itself correlated with input choices, varies within firm or plant over time but remains untreated in known estimation procedures. Similarly, Blundell and Bond (2000) conclude that persistent input series trouble instruments in first-differenced estimators, whereas lagged first differences in extended GMM perform more reasonably. At present, several proposed proxies to productivity compete for the researcher's attention: Investments (Olley and Pakes 1996), intermediate goods (Levinsohn and Petrin 2003) and lagged variables (Blundell and Bond 2000), while adjustments for firm survival and endogenous price also demand inclusion. The estimation framework of the present paper synthesizes these approaches consistently and documents that *individual business prospects and firm-level responses to the competitive environment* are major but so far untreated sources of shocks that vary within firm and over time.

A growing body of micro-econometric research into productivity change provides evidence that the efficiency of plants or firms responds to competitive pressure and rivaling innovations (Tybout and Westbrook 1995, Nickell 1996, Djankov and Hoekman 2000, Pavcnik 2002).[1] The business literature abounds with productivity management techniques: Terms such as supply-chain management, group technology, and lean management including just-in-time, kaizen, or continuous improvement may have replaced older notions such as reorganization or re-engineering and the efficiency-change acronyms of the 1980s (MRP, OPT, or FMS). The idea, however, remains unaltered. In its pursuit of efficient business processes, good management responds to competition and market conditions. In short, investment in productivity-relevant assets is under the management's control and production function estimation should account for it beyond endogenous exit and endogenous price.

[1]Some earlier studies on episodes of trade liberalization identified smaller but still detectable effects (Tybout, Melo and Corbo 1991, Levinsohn 1993).

The present paper advances a parsimonious q-theory model of investment in capital and productivity-relevant assets under convex adjustment costs and endogenous price. The resulting estimation routine employs firm-level investments interacted with sector-level competition variables (such as entry barriers, concentration measures or foreign market penetration) to approximate productivity.

The estimation algorithm remedies the disturbing discrepancies to firm-fixed effects. Capital coefficients on equipment and structures, and coefficients on intermediate inputs, from the present estimator resemble firm-fixed effects estimators. This agreement indicates that the new expectations-proxy to productivity largely captures the firm-specific time-variant effect that used to trouble estimation. While Levinsohn and Petrin (LP) estimates vary widely across bootstraps, the expectations-proxy estimator proposed here yields considerably less volatile estimates.

In the spirit of Olley and Pakes (OP), the complete procedure uses survival to extract additional information on productivity and removes biases from affected coefficients by leading the properly estimated part of the production function one period. Resulting capital coefficients exceed the low OLS estimates in about half the manufacturing sectors. So, the algorithm removes a commonly suspected negative bias in OLS capital coefficients. To the contrary, the shorter LP algorithm would detect lower rather than higher capital coefficients than OLS in the present data. Finally, the estimation algorithm removes time-invariant demand components from the firm-fixed effect. Consequently, productivity *change* is measured properly under common assumptions on price setting behavior (Klette and Griliches 1996), endogenous productivity choice and exit.

This "*eureka*" notwithstanding, some issues remain to be resolved in future research. Unobserved but endogenous final-goods prices may continue to confound the estimate of returns to scale and depress production coefficients jointly. So, estimates of the *level* of scale economies are unidentified. Furthermore, certain discrepancies between relative factor shares in firm-level expenditures and production coefficients prevail. Firm heterogeneity may distort expenditure shares away from marginal products of the mean firm.

The remainder of this paper is organized as follows. Section 1 presents an estimation model based on the assumption that firms set investment schedules for both physical capital and productivity-relevant assets, relegating mathematical details to appendix A. The method is applied to Brazilian manufacturing firm data, which section 2 describes. Section 3 introduces the new proxy variable to productivity—firm-level investment interacted with sector-level competition measures—, and offers bootstrap comparisons to alternative estimators. Section 4 shows that the inclusion of survival correction mitigates a negative bias in capital coefficients and documents that fixed-effect estimates coincide with the new expectations-proxy estimates. Section 5 presents consistent measures of productivity change, while section 6 discusses remaining discrepancies between factor shares and expenditure shares. Section 7 concludes.

1 Estimating Production Functions

Consider a firm i's Cobb-Douglas production function in year t in its logarithmic form

$$z_{i,t} = \beta_L \, l_{i,t} + \beta_K \, k_{i,t} + \beta_M \, m_{i,t} + \nu\omega_{i,t}, \tag{1}$$

where $z_{i,t}$ denotes log output (deflated sales revenues plus production for stock), $l_{i,t}$ is log end-of-year employment, $k_{i,t}$ the log capital stock, $m_{i,t}$ log intermediate goods, and $\nu\omega_{i,t}$ represents log total factor productivity (*TFP*). *TFP* is not observed in the data but known to and partly chosen by the firm's management.

Several biases affect estimates of production coefficients in micro-data.[2] First and foremost, firms choose investment in fixed assets given their productivity. But productivity is not observable to the researcher so that its omission causes a 'transmission bias.' The present theoretical model shows that, if firms can invest both in capital goods and efficiency-relevant aspects of their production process, they may choose to raise or let decay capital and productivity simultaneously. This fact can introduce a positive bias in β_K. Second, Klette and Griliches (1996) show that an error in production function estimates arises from an 'omitted price bias.' This problem occurs when revenue figures are used to approximate output and can result in a demand-side scaling factor that depresses all coefficient estimates jointly. Subsection 1.1 addresses 'transmission bias' and subsection 1.2 discusses 'omitted price bias.' Finally, there is a potential 'selection bias.' Firms with a large capital stock are more likely to remain in business and tolerate lower productivity levels. This can introduce a negative bias in β_K as Olley and Pakes (1996) show. Among other treatments, an unbalanced panel of firms should be considered.

This paper bases production function estimation on a model of the firm that features endogenous productivity change, price setting and exit. The model gives rise to a novel set of productivity proxies—investments interacted

[2] Marschak and Andrews (1944) outline problems early on.

with competition variables—, and addresses unresolved estimation issues related to unobserved time-varying within-firm effects, price setting and survival adjustment in a single framework.

The variable $\Omega_{i,t}$ denotes the total of a firm's tacit knowledge, organizational skills, and efficiency-relevant arrangements embodied in the production process. All of these factors contribute to a firms' *TFP* level. They are not transferrable from one firm to another but can be accumulated within a firm. They depreciate unless cultivated with (net) investment $I^{\Omega}_{i,t}$. Investment $I^{\Omega}_{i,t}$ is chosen at the end of year $t-1$ and becomes fully effective in t. For simplicity, *TFP* is assumed to be

$$TFP_{i,t} = (\Omega_{i,t})^{\nu} \tag{2}$$

for some coefficient $\nu > 0$. As opposed to physical capital accumulation, there is a stochastic factor $\tilde{x}_{i,t}$ to the evolution of organizational knowledge:

$$\Omega_{i,t} = \left[\Omega_{i,t-1}(1-\delta^{\Omega}) + I^{\Omega}_{i,t}\right] \cdot \tilde{x}_{i,t}. \tag{3}$$

The parameter δ^{Ω} expresses the depreciation rate of organizational knowledge. The stochastic factor $\tilde{x}_{i,t}$ captures a firm's efficiency and is assumed to be uncorrelated with its past realizations and factor inputs.

Several recent empirical studies at the level of firms or plants find that product-market competition tends to instill investment in process innovations and that it exerts discipline on managers to "trim their firms' fat" (Nickell 1996, Djankov and Hoekman 2000, Pavcnik 2002). So, productivity is at least partly under the managers' control.

These insights have implications for estimation. Appendix A develops an according q-theory model of investments in capital and productivity with convex adjustment costs, and a slight extension for managerial effort choice. Table 1 presents key assumptions of the model and its implications. The table also compares implications of the present model to those of Olley and Pakes' (1996) framework.

A firm chooses organizational investment $I^{\Omega}_{i,t}$ as a function of the capital stock $K_{i,t-1}$ and the productivity level $\Omega_{i,t-1}$, and depending on market expectations. The model implies that this choice is closely related to the choice of net investment in capital goods. Let $q^{K}_{i,t-1}$ denote Tobin's q for physical capital and $I^{K}_{i,t}$ be net investment in capital goods (gross investment less asset sales and retirements). Just as for investment in efficiency-relevant assets, physical net investment $I^{K}_{i,t}$ is chosen at the end of year $t-1$ and becomes fully effective in t.

By its first-order condition (A.8), organizational investment is a function of the according $q^{\Omega}_{i,t-1}$:

$$I^{\Omega}_{i,t} = (q^{\Omega}_{i,t-1} - 1)\, \Omega_{i,t-1}/\psi^{\Omega}, \tag{4}$$

Table 1: COMPONENTS OF q-THEORY MODEL

Variable	Evolution / Timing	Data	Olley & Pakes
State Variables			
TFP: $(\Omega_{i,t})^{\nu}$	$\Omega_{i,t} = \left[\Omega_{i,t-1}(1-\delta^{\Omega}) + I^{\Omega}_{i,t}\right] \tilde{x}_{i,t}$	no	Markovian[a]
Capital $K_{i,t}$	$K_{i,t} = K_{i,t-1}(1-\delta^{K}) + I^{K}_{i,t}$	yes	same
Control Variables			
Investment $I^{\Omega}_{i,t}$	before $\tilde{x}_{i,t}$ realized (based on $q^{\Omega}_{i,t-1}$)	no	absent[a]
Investment $I^{K}_{i,t}$	before $\tilde{x}_{i,t}$ realized (based on $q^{K}_{i,t-1}$)	yes	same
Survival $\chi_{i,t}$	after $\tilde{x}_{i,t}$ realized	yes	same
Labor $L_{i,t}$	after $\tilde{x}_{i,t}$ realized	yes	same
Implications			
Upward bias in capital coefficient possible			no
Monotonicity of $\Omega_{i,t}$ in $I^{K}_{i,t}$ holds unconditionally			holds for $I^{K}_{i,t} > 0$

[a]Olley and Pakes (1996) consider an exogenous Markov process of *TFP* beyond a firm's control. Alternatively, Ericson and Pakes (1995) allow for a binary choice of *TFP* improvement that affects the Markov process. The current model allows managerial effort to alter the distribution of $\tilde{x}_{i,t}$ as in a standard principal-agent model. Whereas $I^{\Omega}_{i,t}$ is observable to a firm's owner from cash flows, managerial effort is not.

where ψ^{Ω} is a parameter of the adjustment cost function. Conditional on survival, the q^{Ω} for organizational skills and the q^{K} for capital goods are positively related by (A.14):

$$q^{\Omega}_{i,t-1} = \rho_{i,t-1}(\mathbf{D}^{e}_{t-1}) \cdot q^{K}_{i,t-1},$$

where $\rho_{i,t-1} > 0$ is a function of expected market conditions $\mathbf{D}^{e}_{t-1}$ and the expected adjustment path from t on. Note that $q^{\Omega}_{i,t-1}$ monotonically increases in $q^{K}_{i,t-1}$.

Using the first-order condition (A.8) for capital investment $q^{K}_{i,t-1} = 1 + \psi^{K} I^{K}_{i,t}/K_{i,t-1}$ and plugging (4) into (3), yields

$$\Omega_{i,t} = \left\{(1-\delta^{\Omega}) + \left[\rho_{i,t-1}(\mathbf{D}^{e}_{t-1})\ (1 + \psi^{K} I^{K}_{i,t}/K_{i,t-1}) - 1\right]/\psi^{\Omega}\right\} \cdot \Omega_{i,t-1} \cdot \tilde{x}_{i,t}. \quad (5)$$

Equation (5) underlies the subsequent removal of 'transmission bias' from production coefficients. Moreover, equation (5) also clarifies that, under endogenous productivity choice with convex adjustment costs, $\Omega_{i,t}$ monotonically increases in $I^{K}_{i,t}$ for any given level of $K_{i,t-1}$ and $\Omega_{i,t-1}$.

Under the alternative assumption made by Olley and Pakes (1996) that productivity follows a Markov process beyond managerial control, monotonicity only holds for $I^{K}_{i,t} > 0$ (Pakes 1996). These assumptions have important implications for empirical implementation. Non-positive net investment occurs frequently in firm or plant data. The median Brazilian manufacturer between 1986 and 1998, for instance, conducts zero net investment in equipment (see table 2) so that requiring $I^K_{i,t} > 0$ for estimation results in a considerable loss of observations. The presence of endogenous productivity choice under convex adjustment costs, however, justifies the retention of observations with non-positive net investment.

1.1 Correction for 'Transmission Bias'

A transmission bias in the capital stock arises because both investment and the exit choice are correlated with $\nu\omega_{i,t}$. By (3), the log productivity index $\nu\omega_{i,t}$ can be written as

$$\nu\omega_{i,t} = h(I^K_{i,t}, k_{i,t}, \mathbf{D}_t) + \beta_{0,i} + \nu\xi_{i,t} \tag{6}$$

for some function $h(\cdot)$. $\beta_{0,i}$ is a firm-specific mean of productivity shocks, and $\xi_{i,t}$ is a serially uncorrelated shock to productivity with mean zero and constant variance across firms in a sector. Both $\beta_{0,i}$ and $\xi_{i,t}$ are known to the firm when it chooses variable factor inputs (labor, intermediate goods) and investments $I^K_{i,t+1}$ and $I^\Omega_{i,t+1}$ for next period. While entirely known to the firm's management, $\nu\omega_{i,t}$ is not observable to the researcher. There is no variable for a firm's expectations but one may suppose that firms are fairly well informed about looming domestic market outcomes, especially in samples with medium-sized to large firms such as the present one. So, the vector of current market conditions $\mathbf{D}_t$ is taken as a proxy for past expectations $\mathbf{D}^e_{t-1}$. Although different in its underlying assumptions from the model behind Olley and Pakes (1996), the present framework of endogenous investment in productivity-relevant assets suggests a structurally similar estimation approach.

The first regression equation follows by using (6) in (A.5),

$$\begin{aligned} z_{i,t} &= \beta_{0,i} + \beta_L\, l_{i,t} + \beta_M\, m_{i,t} + \beta_K\, k_{i,t} + h(I^K_{i,t}, k_{i,t}, \mathbf{D}_t) + \nu\xi_{i,t} + \epsilon_{i,t} \\ &\equiv \beta_{0,i} + \beta_L\, l_{i,t} + \beta_M\, m_{i,t} + \phi(I^K_{i,t}, k_{i,t}, \mathbf{D}_t) + \nu\xi_{i,t} + \epsilon_{i,t}. \end{aligned} \tag{7}$$

Only part of the regression equation is linear. The term $\phi(\cdot) \equiv \beta_K\, k_{i,t} + h(\cdot)$ arises because the effect of log *TFP* on output cannot be separated from the effect of physical capital on output as long as their correlation is not removed. The coefficient estimates for β_L and β_M, on the other hand, are consistent if $\phi(\cdot)$ is approximated well.

The competitive environment reflected in $\mathbf{D}_t$ depends on the productivity distribution of producers. Market concentration, government policies such as antitrust and tariff measures, aggregate demand, or foreign competition all respond to the prevailing productivity distribution. To avoid simultaneity issues from this source, I use the nominal exchange rate and foreign producer price indices at the sector level as instrumental variables to predict foreign competition, aggregate demand, and tariff barriers. Firms are very limited in their ability, if not unable, to base their productivity-relevant investment on the future exchange rate and future innovations to foreign producer costs.

Next, estimate the probability of a firm's survival given today's information. Theory predicts that survival occurs as long as the realization of $\xi_{i,t}$ exceeds a minimal level that depends on market expectations and installed capital so that $\omega_{i,t} \geq \underline{\omega}(k_{i,t}, \mathbf{D}_t)$ (see appendix A). The probability of survival is derived in (A.16) in appendix A and becomes

$$Pr\,(\chi_{i,t+1} = 1|\cdot) = Pr\,(\omega_{i,t} \geq \underline{\omega}(k_{i,t}, \mathbf{D}_t)) = P(I^K_{i,t}, k_{i,t}, \mathbf{D}_t) \tag{8}$$

in the present context. Equation (8) is the second estimation equation. A probit and a logit model estimate it.

Finally, to obtain a consistent estimate of the capital coefficient β_K, exploit information on the expected contribution of capital to production one period in advance. Consider $z_{i,t+1} - \beta_{0,i} - \beta_L\, l_{i,t+1} - \beta_M\, m_{i,t+1}$. Conditional on survival, the expectation of this term is

$$\begin{aligned}
&\mathbb{E}\,[z_{i,t+1} - \beta_{0,i} - \beta_L\, l_{i,t+1} - \beta_M\, m_{i,t+1}\,|k_{i,t}, \omega_{i,t}, \mathbf{D}_t, \chi_{i,t+1} = 1] \\
&\quad = \beta_K\, k_{i,t+1} + \mathbb{E}\,[\omega_{i,t+1}\,|k_{i,t}, \omega_{i,t}, \mathbf{D}_t, \chi_{i,t+1} = 1] \\
&\quad = \beta_K\, k_{i,t+1} + \int_{\underline{\omega}(k_{i,t}, \mathbf{D}_t)} \omega_{i,t+1} \frac{f\,(\omega_{i,t+1}|\omega_{i,t})}{Pr\,(\chi_{i,t+1} = 1|\cdot)}\, d\omega_{i,t+1}
\end{aligned}$$

by equations (1), (6), and (8). $P(\cdot)$, a function of $\mathbf{D}_t$, can approximate the cutoff $\underline{\omega}(k_{i,t}, \mathbf{D}_t)$.[3] In other words, we can view the productivity expectation $\mathbb{E}\,[\omega_{i,t+1}\,|k_{i,t}, \omega_{i,t}, \mathbf{D}_t, \chi_{i,t+1} = 1]$ as a function of $\underline{\omega}(\cdot)$ and $\omega_{i,t}$ or as a function $g\,(P(\cdot), \phi(\cdot) - \beta_K\, k_{i,t})$. So,

$$\begin{aligned}
&z_{i,t+1} - \beta_{0,i} - \beta_L\, l_{i,t+1} - \beta_M\, m_{i,t+1} \\
&\qquad = \beta_K\, k_{i,t+1} + g\,(P(\cdot), \phi(\cdot) - \beta_K\, k_{i,t}) + \nu\xi_{i,t+1} + \epsilon_{i,t+1}.
\end{aligned} \tag{9}$$

$\xi_{i,t+1}$ is the unanticipated innovation in $\omega_{i,t+1}$. Hence, it is not correlated with net investment $I^K_{i,t}$ or tomorrow's log capital stock $k_{i,t+1}$, and the estimate of β_K is consistent under the assumptions made. Equation (9) is the third estimation equation.

[3] Under regularity conditions (the density of $\xi_{i,t+1}$ needs to be positive in a neighborhood around $\xi_{i,t}$), $\underline{\omega}(\cdot)$ can be inverted in capital and expressed as a function of $\mathbf{D}_t$ and $P(\cdot)$, which is a function of $\mathbf{D}_t$ in turn.

A third-order polynomial expansion $\sum_{m=0}^{3}\sum_{n=0}^{3-m}\beta_{m,n}(\hat{P})^m(\hat{h})^n$ approximates $g\left(P(\cdot),h(\cdot)\right)$ in equation (9). The capital coefficient enters equation (9) twice: in the additive terms, and through $\hat{h}(\cdot)=\hat{\phi}(\cdot)-\beta_K\, k_{i,t}$. I estimate the equation with non-linear least squares, using fixed-effects estimates of equation (7) as starting values. Subtracting the fixed effect $\beta_{0,i}$ from $z_{i,t}$ on the left hand side reduces the fit in some sectors. However, the error term needs to be identically distributed for the bootstrap to follow. This requires the subtraction of $\beta_{0,i}$.

1.2 Partial Correction for 'Omitted Price Bias'

Production function estimation is consistent if proper quantity measures for output and inputs can be used. However, a source of bias remains for estimates of economies of scale if that is not the case. The bias arises because price is unknown but endogenous in imperfectly competitive markets. Harrison (1994) discusses the problem of markups in input prices, and Klette and Griliches (1996) address the problem of final-goods price markups.

The total of a firm's sales and production for stock, deflated by sector-specific price indices, approximates output. So, the dependent variable in the first regression equation (7) is in fact $p_{i,t}+z_{i,t}-\bar{p}_t$, where $p_{i,t}$ denotes the log of firm i's price and $\bar{p}_t$ the value of the price index for deflation. By demand (A.3), the difference between a firm's price and market price is $p_{i,t}-\bar{p}_t = -(1-\alpha)d_{i,t}+(1-\alpha)(\bar{\theta}_t-\bar{p}_t)$, where $-1/(1-\alpha)\in(-\infty,-1)$ approximates price elasticity of demand and $\bar{\theta}_t$ denotes the log of market-wide demand. Because of this relationship and since $d_{i,t}=z_{i,t}$ in equilibrium, the *de facto* regression is

$$\begin{aligned}(p_{i,t}+z_{i,t}-\bar{p}_t) &= \alpha z_{i,t}+(1-\alpha)(\bar{\theta}_t-\bar{p}_t)\\ &= \alpha\beta_{0,i}+(1-\alpha)(\bar{\theta}-\bar{p})\\ &\quad +\alpha\beta_L\, l_{i,t}+\alpha\beta_M\, m_{i,t}+\alpha\phi(I^K_{i,t},k_{i,t},\mathbf{D}_t)\\ &\quad +(1-\alpha)(\Delta\bar{\theta}_t-\Delta\bar{p}_t)+\alpha\nu\xi_{i,t}+\alpha\epsilon_{i,t},\end{aligned} \tag{10}$$

rather than (7). Here, the log of market-wide demand for close substitutes $(1-\alpha)(\bar{\theta}_t-\bar{p}_t)$ is decomposed into a preference based component $(1-\alpha)(\bar{\theta}-\bar{p})$ that does not vary over time, and into a time-varying component $(1-\alpha)(\Delta\bar{\theta}_t-\Delta\bar{p}_t)$ that moves with the market conditions and the business cycle ($\Delta\bar{\theta}_t\equiv\bar{\theta}_t-\bar{\theta}$ and $\Delta\bar{p}_t\equiv\bar{p}_t-\bar{p}$).

The demand-side parameter α confounds the estimate of returns to scale by appearing in front of $z_{i,t}$. Klette and Griliches (1996) propose to use the sum of all firms' sales to approximate market-wide demand and to include it explicitly in the regression.Their purpose is to correct the scale estimate. Here, however, the focus lies on endogenous productivity choice, and there are theoretical and practical reasons not to use Klette and Griliches' full correction but rather only a fixed-effects variant. The present estimation framework implies that the fixed-effects estimator $\alpha\beta_{0,i} + (1-\alpha)(\bar{\theta} - \bar{p})$ absorbs the time-invariant demand component $\bar{\theta}$ and that the time-varying demand component $\Delta\bar{\theta}_t$ becomes part of the expectations proxy $\alpha\phi(I^K_{i,t}, k_{i,t}, \mathbf{D}_t) + (1-\alpha)(\Delta\bar{\theta}_t - \Delta\bar{p}_t)$.

A firm's investment in efficiency-relevant assets $\omega_{i,t}$ depends on market expectations (see (A.2) and (A.10)) in appendix A). Similarly, the contractable efficiency choice of a manager depends on market conditions (A.18). If these market expectations are rational and firms are able to anticipate demand well, the coefficient on log sector-wide demand, which is part of the vector $\mathbf{D}_t$, will capture efficiency choice rather than the omitted price effect.

Interpreting the coefficient on sector-wide demand as a mere measure of the demand elasticity, and taking equation (10) at face value, implies that the predicted effect of deflated sector-wide demand $(1-\alpha)(\Delta\bar{\theta}_t - \Delta\bar{p}_t)$ should be removed from firm-level productivity estimates. Estimation in section 4 shows, however, that the coefficient on log aggregate demand would imply an unreasonably small demand elasticity $-1/(1-\alpha)$ in most sectors. In fact, coefficient estimates imply $1-\alpha > 1$ but $\alpha > 0$, an impossibility. Conversely, this finding indicates that market expectations can go a long way in explaining productivity choice. The coefficient estimate for $(1-\alpha)$ likely captures both the price elasticity of demand and the effect of current demand on realizations of productivity choice.

The present estimation framework addresses endogenous investment in productivity-relevant assets. Up to a correction factor for scale economies, unbiased production function coefficients result and consistent measures of firm-level *TFP change* can be inferred.

2 Data

The Brazilian statistical bureau *IBGE* surveys manufacturing firms and plants annually in its *Pesquisa Industrial Anual* (*PIA*). Firm data arguably reflect unobserved characteristics and inputs such as managerial ability and effort more closely than do plant data. So, firm data are used here. The firm sample from 1986 to 1995 (with the year 1991 missing due to a federal austerity program), and its extension through 1998, is representative for medium-sized to large manufacturing companies but not necessarily for the Brazilian manufacturing sector as a whole. This section summarizes data characteristics and highlights elements of the panel construction. Appendix B provides a brief description of the statistical bureau's sampling method.[4]

The present analysis mostly compares the five sectors with the largest number of firm-year observations at *nível 50*: (08) Machinery, equipment and installations; (14) Wood sawing, wood products and furniture; (22) Textiles; (26) Plant product processing (including rice and wheat milling, fruit and vegetable processing, and tobacco); and (31) Other food and beverage manufacturing (including animal feeds, other food and beverage manufacturing). Since sectors 26 and 31 embrace a diverse group of manufacturers, less emphasis will be put on production function estimates for those. Together, the five largest sectors comprise 21,465 firm-year observations of the total 60,656 observations. To infer firm-level productivity and its evolution in section 5, I estimate production functions for all 27 manufacturing sectors at *nível 50.*

PIA offers precise longitudinal information for every firm. Special variables summarize a firm's state of operation and make sure that observations with missing economic information are not confounded with shutdown or temporary suspension of production. Brazilian manufacturers between 1986 and 1998 "mothball" for extended periods of time. Among the 9,500 firms with valid observations, more than 1,100 state in at least one year that they suspended production temporarily or for the entire year. This information offers an appropriate survival indicator, as distinct from a non-missing indicator, for the estimation procedure.

Economic variables in *PIA* include sales figures and changes in final goods stocks, costs of inputs, salaries, employment of blue- and white-collar workers, and several variables related to investment and the capital stock. Firms in *PIA* also report their acquisitions of foreign equipment until 1995 and their purchases of foreign intermediate goods since 1996. Output and domestic inputs are deflated with sector-specific wholesale price indices. Capital stock figures and investments are deflated with economy-wide wholesale price indices. There is no producer price index for Brazil. A perpetual inventory method, which controls for changes to accounting law in 1991, yields the overall capital stock.

Table 2 presents summary statistics for the five largest sectors. A sizable number of observations exhibits missing values for several variables. Except for intermediate steps in the perpetual inventory method for capital stock figures, no variables are imputed.

Sector classifications in *PIA* would allow for the estimation of production functions at a level that corresponds to three *ISIC rev. 3* digits (*nível 100*). However, large firms in *PIA* are likely to offer product ranges beyond nar-

[4] Muendler (2003) documents the construction of an unbalanced firm panel from *PIA* in detail.

Table 2: Summary Statistics for largest five sectors

	Mean (1)	S.dev. (2)	Median (3)	Obs. (4)
Output	26.412	66.955	7.060	21,465
Value added	15.196	42.967	3.529	19,933
Total employment	677.266	1,102.038	300	17,362
Blue-collar employment	468.528	3,077.856	176	20,894
White-collar employment	164.808	373.944	50	17,574
Total capital	14.404	41.604	3.374	17,912
Equipment	4.367	13.145	.760	17,923
Structures	10.027	34.495	2.273	17,927
Intermediate goods	12.572	33.258	2.836	20,862
Total investment	1.540	9.521	.046	20,118
Equipment investment	.508	4.653	0	20,118
Structures investment	1.032	7.715	.019	20,118
Foreign equipment share	.023	.098	0	18,800
Foreign intm. goods share	.013	.073	0	24,123
Foreign market penetration	.049	.056	.026	24,661
Nominal tariff	.352	.246	.257	24,661
Aggregate demand	10,196.940	3,329.918	10,563.770	24,661

Data: *Pesquisa Industrial Annual* 1986-1998 from sectors (08) *Machinery*, (14) *Wood and furniture*, (22) *Textiles*, (26) *Plant products*, (31) *Other food and beverages*.
Economic figures in million Reais, August 1994; employment in number of persons; foreign input shares, market penetration and tariffs as fractions.

rowly defined sector limits. Data at more aggregate levels also provide more variation in the cross section because variables related to the market environment become available for two or more subsectors within several sectors. Those variables provide identification. Moreover, switching from the three to the two-digit level increases the number of observations per estimation considerably. So, I carry out estimation at two *ISIC3* digits (*nível 50*).

3 Comparisons to Alternative Estimators

Among the estimators typically employed in production function estimation are OLS, fixed effects, instrumental variable estimators, and the Olley and Pakes (1996) and Levinsohn and Petrin (2003) estimators in the presence or absence of observations with non-positive investment. Firm- or plant-level studies show, for the most part, that the fixed-effects estimator exhibits the starkest differences to alternative estimators. Levinsohn and Petrin (2003), for instance, document for a sample of Chilean manufacturing plants in four sectors: "The fixed effects estimator is in the most pronounced disagreement with other estimators as it rejects compatibility with *every* other estimator in every industry at the 1% level of significance. Previous results suggest the existence of a persistent shock which is highly correlated with input choices. This results says that this persistent shock seems to vary within-firm over time."

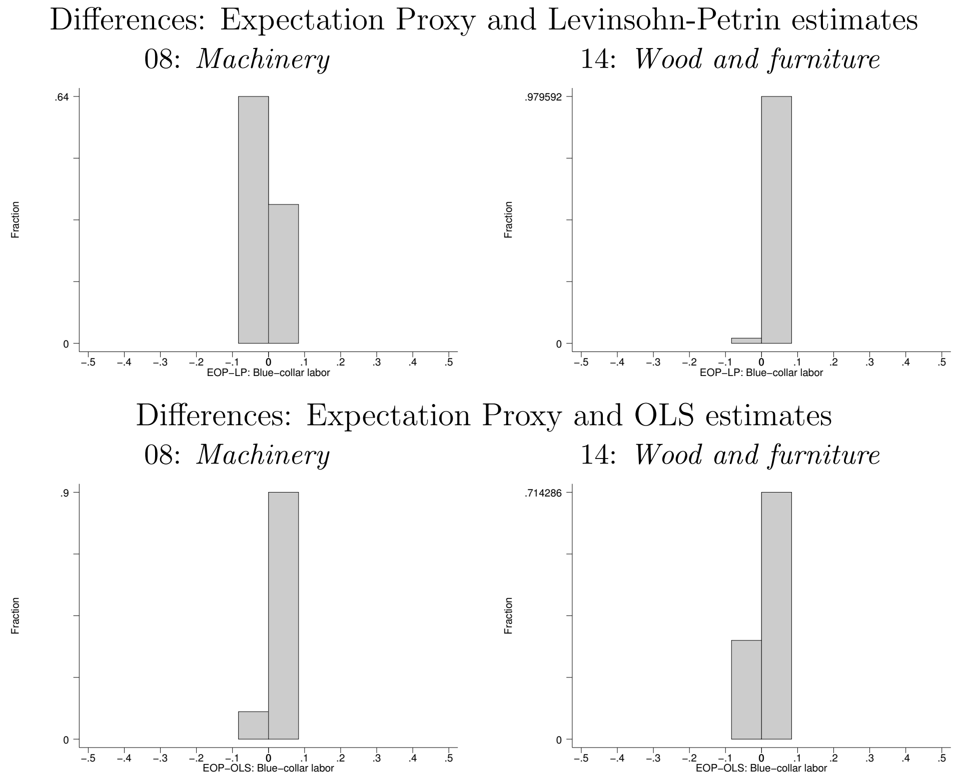
Firm-level expectations about individual business prospects and possible responses to the competitive market environment lie behind the persistent shock which varies within firms and over time. Firm-level net capital investment interacted with a sector-level competition variable (such as foreign market penetration) is a leading candidate to capture a firm's individual market expectations and to correct for 'transmission bias.' To establish this proxy variable, the present section compares the use of firm-level investment interacted with sector-level competition (as proposed here) to intermediate inputs (as proposed by Levinsohn and Petrin 2003) and to the OLS estimator. To focus the comparison, I use the shorter Levinsohn and Petrin (2003) correction algorithm in this section. The extended Olley and Pakes (1996) approach and a comparison to fixed effects estimation is deferred to the following section 4.

Instead of approximating firm-level productivity through a polynomial in covariates as in equation (7), Levinsohn and Petrin (2003) regress the output variable and all input variables that are supposedly unaffected by 'transmission bias' on intermediate goods (the proxy variable) and the capital stock. They subtract the predictions from the observed variables and run the according short regression of the production function

$$z_{i,t} - \hat{z}_{i,t} \quad = \quad \beta_{bl}\,(l^{bl}_{i,t} - \hat{l}^{bl}_{i,t}) + \beta_{wh}\,(l^{wh}_{i,t} - \hat{l}^{wh}_{i,t}) + \epsilon_{i,t}, \tag{11}$$

where variables with hats denote predictions from a linear regression on $m_{i,t}$ and $k_{i,t}$. Labor is split into blue-collar and white-collar employment to improve the fit.

To obtain consistent coefficient estimates for intermediate inputs and capital, according moment conditions can be applied: Under the assumptions made, productivity shocks are orthogonal to the current capital stock and lagged variable inputs (intermediate goods, labor). The correlation between the unpredictable part of productivity ($\widehat{\nu\omega_{i,t}}(\breve{\beta}_M, \breve{\beta}_K) = z_{i,t} - \widehat{\beta}_{bl}\, l^{bl}_{i,t} - \hat{\beta}_{wh}\, l^{wh}_{i,t} - \breve{\beta}_M\, m_{i,t} - \breve{\beta}_K\, k_{i,t}$ from the first stage) and the current capital stock or any lagged variable input is conditioned to be zero. The according GMM estima-



Data: *Pesquisa Industrial Annual* 1986-1998. Estimates from 50 bootstraps.

Figure 1: **Bootstrapped blue-collar labor coefficients**

tor minimizes

$$Q(\beta_M, \beta_K) = \min_{\beta_M, \beta_K} \sum_{h=1}^{4} \left(\sum_i \sum_t \nu\xi_{i,t}(\check{\beta}_M, \check{\beta}_K) \cdot \upsilon_{h;i,t} \right)^2 \tag{12}$$

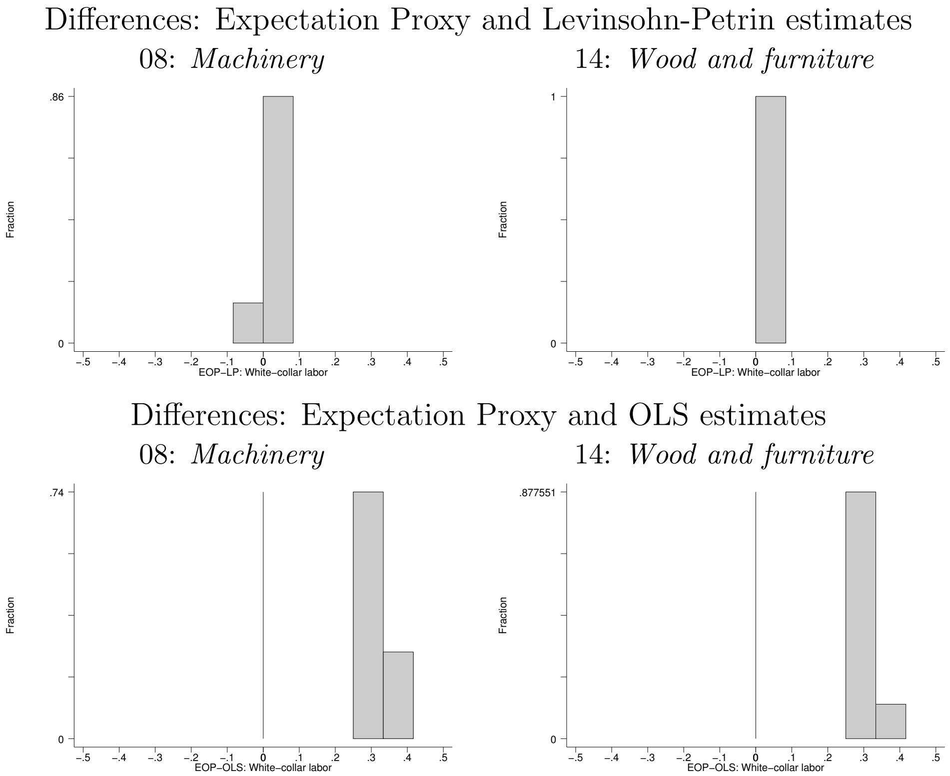
over estimates of β_M and β_K, where the counter h in $\upsilon_{h;i,t}$ stands for the four variables $k_{i,t}, m_{i,t-1}, l^{bl}_{i,t-1}$ and $l^{wh}_{i,t-1}$. Starting values for $\check{\beta}$ and $\check{\beta}$ are estimates from the $\hat{z}_{i,t}$ regression at the outset of the first step. Non-linear least squares are used for the GMM iteration.

A preferable alternative single-variable proxy for productivity, instead of $m_{i,t}$, is firm-level investment $I^K_{i,t}$ interacted with some current sector-level competition variable $D_{i,t}$ such as, for instance, foreign market penetration (the following section 4 presents multivariate proxies). Under similar theoretical assumptions to those underlying the moment condition $\mathbb{E}_{t-1}\left[\nu\omega_{i,t} \cdot m_{i,t-1}\right] = 0$, investment $I^K_{i,t}$ chosen at the end of t–1 (or during t) and effective by the end of t is uncorrelated with end-of-year productivity $\nu\omega_{i,t}$. So, $\mathbb{E}_{t-1}\left[\nu\omega_{i,t} \cdot I^K_{i,t}\right] = 0$

Table 3: Comparison among Alternative Production Function Estimates

	Exp. Proxy		LP		OLS	
	Coef.	SE^a	Coef.	SE^a	Coef.	SE^a
	(1)	(2)	(3)	(4)	(5)	(6)
(08) Machinery						
Blue-collar labor	.251	.031	.254	.033	.221	.041
White-collar labor	.303	.024	.287	.025	-.008	.027
Intermediate goods	.372	.022	8.21e-06	.212	.605	.03
Capital	.143	.055	.373	.239	.376	.033
Inv. * For. penetr.	3.00e-07	7.80e-07				
Obs.		2,622		2,694		2,694
(14) Wood and furniture						
Blue-collar labor	.376	.025	.365	.026	.364	.034
White-collar labor	.216	.02	.199	.018	-.083	.027
Intermediate goods	.34	.019	.087	.17	.616	.026
Capital	.00002	.019	.213	.103	.334	.023
Inv. * For. penetr.	1.00e-05	.0003				
Obs.		2,723		2,835		2,835
(22) Textiles						
Blue-collar labor	.264	.027	.281	.023	.224	.032
White-collar labor	.219	.023	.203	.021	-.061	.023
Intermediate goods	.462	.024	.124	.077	.679	.023
Capital	.068	.198	.197	.056	.31	.024
Inv. * For. penetr.	7.63e-08	.003				
Obs.		3,190		3,258		3,258
(26) Plant products						
Blue-collar labor	.256	.023	.211	.022	.288	.033
White-collar labor	.238	.021	.228	.019	-.092	.025
Intermediate goods	.378	.025	.655	.208	.549	.027
Capital	.112	.061	2.22e-28	.187	.449	.026
Inv. * For. penetr.	8.52e-07	5.14e-07				
Obs.		2,734		2,764		2,764
(31) Other food and beverages						
Blue-collar labor	.275	.022	.232	.023	.221	.03
White-collar labor	.229	.02	.21	.021	-.029	.023
Intermediate goods	.34	.021	.557	.23	.608	.025
Capital	.184	.03	.06	.148	.391	.025
Inv. * For. penetr.	2.31e-07	2.09e-07				
Obs.		3,335		3,431		3,431

[a]Based on 50 bootstraps.



Data: *Pesquisa Industrial Annual* 1986-1998. Estimates from 50 bootstraps.

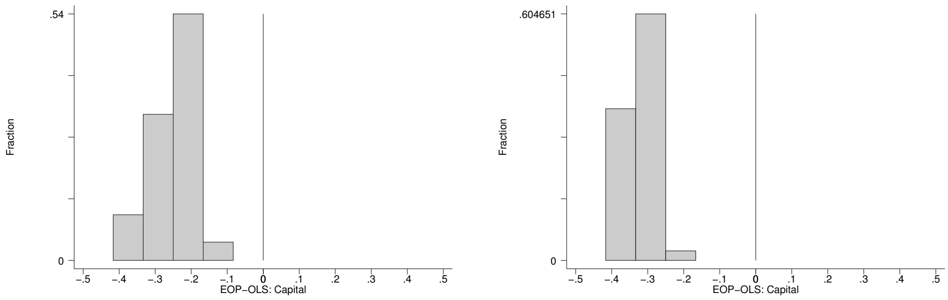
Figure 2: **Bootstrapped white-collar labor coefficients**

To avoid a simultaneity problem from the fact that sector-level competition responds to the prevailing productivity, the nominal exchange rate and foreign producer price indices at the sector level serve as instrumental variables to predict foreign market penetration—the sector-level competition variable used here. For firms, moves in the nominal exchange rate and innovations in foreign producer costs are largely unforeseeable at the time of their investment in productivity-relevant assets. So, instrumented foreign market penetration $\hat{D}_{i,t}$ is uncorrelated with $\nu\omega_{i,t}$. In short, $\mathbb{E}_{t-1}[\nu\omega_{i,t} \cdot I^K_{i,t}\hat{D}_{i,t}] = 0$. Purely domestic competition variables, such as Herfindahl indices of industry concentration for instance, are arguably less akin to instrumentation and therefore omitted.

Table 3 presents the results. Although the coefficient on the single expectations proxy, investment interacted with foreign market penetration, is not significantly different from zero, the use of the proxy yields plausible results for the actual production function coefficients. (The use of multiple proxies in the next section leads to significance of several proxies, see table 5.) The fact

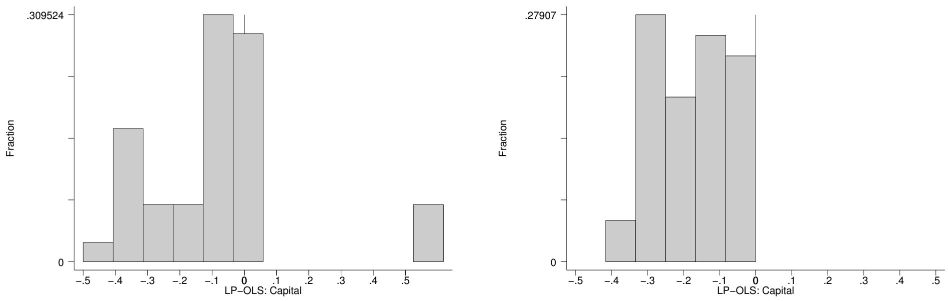
Differences: Expectation Proxy and OLS estimates

08: *Machinery* 14: *Wood and furniture*



Differences: Levinsohn-Petrin and OLS estimates

08: *Machinery* 14: *Wood and furniture*

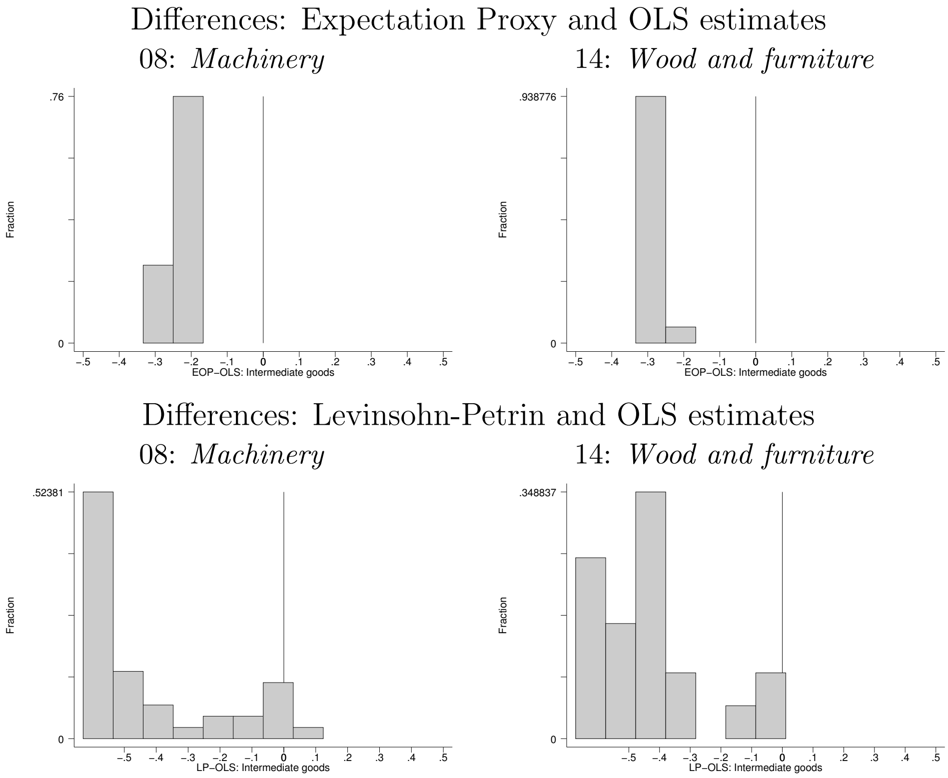


Data: *Pesquisa Industrial Annual* 1986-1998. Estimates from 50 bootstraps.

Figure 3: **Bootstrapped capital coefficients**

that the expectations proxy receives only a very small coefficient estimate is encouraging: Coefficients on physical factor inputs account for almost all of the variation in output, the proxy does not take away from that, while still clearing the coefficient estimates of 'transmission bias.'

The differences between OLS, Levinsohn and Petrin (LP), and expectations proxy estimation suggest underlying biases that are consistent with the generally asserted productivity experience of the Brazilian manufacturing sector. Figures 1 through 4 display histograms of differences between coefficient estimates from 50 bootstraps. The figures compare the frequencies of differences across the three production function estimators for the machinery (08) and the wood and furniture (14) sectors. In general, the shape of the distributions corroborates the findings that table 3 suggests: All three estimators largely agree on the blue-collar labor coefficient, only OLS suggests implausible negative coefficients on white-collar labor, both expectations-proxy and LP estimation suggest *lower* capital and intermediate goods coefficients than OLS. However,



Data: *Pesquisa Industrial Annual* 1986-1998. Estimates from 50 bootstraps.

Figure 4: **Bootstrapped intermediate goods coefficients**

expectations proxy estimation yields sharper and less volatile estimates than LP. I discuss the likely reasons in turn.

Figures 1 and 2 show that neither the blue-collar nor the white-collar labor coefficients differ between the expectations proxy estimation and the LP estimation. Wald tests on the coefficients in table 3 confirm for four out of five sectors (sector 26 being the exception) that labor coefficients coincide under expectations proxy and LP estimation. Also, the OLS coefficient estimate for blue-collar labor mostly coincides with the other two estimates. However, the OLS coefficient on white-collar labor would yield an implausible negative coefficient. The reason is likely that white-collar labor was valuable during the period of macroeconomic instability until around 1994, when production efficiency was low but financial operations and skillful accounting would mitigate or even exploit the otherwise adverse effects of hyperinflation. As prices stabilized and foreign competition intensified, manufacturers raised their productivity and shed white-collar labor that was no longer needed for core operations.

As a consequence of this experience, we can expect white-collar employment to be negatively related to productivity in Brazilian manufacturing during the 1990s.

The bootstraps show for capital coefficients that, in four out of five sectors, both the expectations proxy estimator and the LP estimator yield *lower* capital coefficients than OLS regressions. Figure 3 also illustrates that the expectations proxy estimator yields sharper and less volatile estimates. Taken at face value, the OLS estimator seems to suffer from a positive rather than an often suspected negative bias. A positively biased OLS capital coefficient is also found in other data (Mairesse and Hall 1996, Pavcnik 2002, Levinsohn and Petrin 2003) under alternative estimation methods. The proposed theoretical framework of simultaneous capital and productivity choice highlights precisely the likely positive bias in the capital coefficient. When an individual firm expects particularly favorable business prospects, it will invest both in a larger equipment stock and higher process efficiency.

The next section 4, however, will show that correcting for survival in the style of Olley and Pakes frequently turns the apparently positive bias in OLS estimates into a negative bias. Capital-rich firms are more likely to survive an adverse productivity shock so that there is a negative 'transmission bias' in capital coefficients among survivors. This suggests that the inclusion of survival estimation in the Olley and Pakes (1996) algorithm, which Levinsohn and Petrin (2003) omit, tends to leave the problem of negative biases in capital coefficients unresolved. Table 6 shows that the OLS equipment coefficient exhibits a negative bias in two out of five sectors (14, 26) and that the OLS structures coefficient has a negative bias in three out of five sectors (08, 14, 22). The reason is that exiting firms have lower productivity and lower capital stocks, introducing an artificial negative correlation between capital and productivity among survivors.

Finally, coefficients on intermediate goods exhibit a very similar pattern to the capital coefficients. Both the expectations proxy estimator and the LP estimator yield *lower* intermediate goods coefficients than OLS regressions. Again, figure 4 illustrates that the expectations proxy estimator yields sharper and less volatile estimates. The revealed positive bias in OLS estimates likely stems from the fact that firms that engage in outsourcing to a larger degree also tend to be the more efficient firms. Outsourcing (*terceirização*) became a widely discussed and often pursued business strategy during the 1990s in Brazil. As opposed to the capital coefficients, where the complete Olley and Pakes algorithm yields different assessments of the OLS bias, the bias in the intermediate-goods coefficient is found to be the same. Table 6 shows that the OLS intermediate-goods coefficient exhibits a positive bias in all five sectors.

To conclude, the new single-variable proxy to productivity—firm-level investment interacted with sector-level competition—yields similar but sharper and less volatile estimates than the alternative Levinsohn and Petrin proxy (intermediate goods). This establishes the expectations proxy as a viable alternative. Its main benefit, however, is documented in the following section. The extended Olley and Pakes estimates under the new proxy resembles fixed-effects estimates. This agreement indicates that the new expectations-proxy to productivity largely captures the firm-specific time-variant effect that used to trouble estimation.

4 Complete Production Function Estimation

The preceding section documents that firm-level investment interacted with sector-level competition does well as an expectations proxy variable, and can improve the precision of estimates over alternative proxies. However, the Levinsohn and Petrin algorithm neglects the information from survival and exiting behavior. But the observation of survival reveals important information on a firm. In fact, the present section shows that the detected bias in OLS capital coefficients is more frequently negative under the survival-adjusting Olley and Pakes algorithm, whereas the shorter Levinsohn and Petrin algorithm in the previous section would mostly find a surprising positive bias. Most importantly, however, the Olley and Pakes estimates under the new proxy resemble or even coincide with fixed-effects estimates. So, the use of firm-level investment interacted with sector-level competition as a proxy to productivity arguably removes the firm-specific time-variant effect that used to confound estimation.

Both Olley and Pakes (1996) and Levinsohn and Petrin (2003) base their latter-step estimation on the condition that productivity innovation is orthogonal to current capital input and lagged intermediate goods inputs. In addition, Olley and Pakes (1996) explicitly use survival information to conduct the latter-step corrections (equations (8) and (9)) in their procedure. The present framework of endogenous productivity choice is more akin to the use of investment as a proxy variable and to the explicit inclusion of survival probabilities in the estimation.

Production function (1) is augmented to account for all factors that are available in the data and estimated for 27 sectors under the restriction that factor elasticities are constant between 1986 and 1998. The first regression equation is

$$
\begin{aligned}
z_{i,t} &= \beta_{0,i} + \beta_M \, m_{i,t} + \beta_{bl} \, l^{bl}_{i,t} + \beta_{wh} \, l^{wh}_{i,t} \\
&\qquad + \phi(I^K_{i,t}, I^S_{i,t}, a_{i,t}, k_{i,t}, s_{i,t}; \kappa^f_{i,t}, \mu^f_{i,t}; \mathbf{D}_t) + \xi_{i,t} + \epsilon_{i,t} \qquad (13)
\end{aligned}
$$

similar to (7). It is a linear firm-fixed effects regression. Capital is decomposed into equipment $k_{i,t}$ and structures $s_{i,t}$, and so is net investment $(I^K_{i,t}, I^S_{i,t})$. $a_{i,t}$ denotes a firm's log age. A polynomial series estimator of fourth order approximates $\phi(I^K_{i,t}, I^S_{i,t}, a_{i,t}, k_{i,t}, s_{i,t}; \kappa^f_{i,t}, \mu^f_{i,t}; \mathbf{D}_t)$.

Variables $\mathbf{D}_t$ that characterize a firm's competitive environment (foreign market penetration, the economy-wide real exchange rate, nominal tariffs, aggregate demand and the annual inflation rate) partly approximate investments in productivity-relevant assets. The interaction of these variables with the firms' physical investment in equipment and structures is intended to capture both general business prospects and the firms' individual expectations about them. To avoid a simultaneity problem from the fact that market conditions $\mathbf{D}_t$ respond to prevailing productivity, the nominal exchange rate and foreign producer price indices at the sector level serve as instrumental variables to predict foreign market penetration and nominal tariffs. To firms, moves in the nominal exchange rate and innovations in foreign producer costs are largely unforeseeable at the time of their investment in productivity-relevant assets.

To minimize problems of measurement error in inputs, the shares of foreign equipment $\kappa^f_{i,t}$ and foreign intermediate inputs $\mu^f_{i,t}$ are regressors in $\phi(\cdot)$. The variable κ^f is available for 1986 through 1995, and μ^f from 1996 to 1998. Neither year dummies nor time trend variables were significant when included. These findings lend support to the assertion that the drop in the sample in 1996 does not affect productivity estimates.

Next, the probability of a firm's survival is estimated given current information. This probability is given by (8)—based on (A.16) in appendix A—and becomes

$$
Pr\,(\chi_{i,t+1} = 1|\cdot) = P(I^K_{i,t}, I^S_{i,t}, a_{i,t}, k_{i,t}, s_{i,t}; \mathbf{D}_t), \qquad (14)
$$

in the present context. I estimate two independent logit and probit functions for the pre-1991 data and for the post-1991 data, taking into account that the shutdown probabilities may have changed systematically after trade liberalization. Contrary to the general finding that time indicators are not significant, the fit improves in this case.[5] Probabilities are estimated over a fourth-order polynomial in $(I^K_{i,t}, I^S_{i,t}, a_{i,t}, k_{i,t}, s_{i,t})$ and $\mathbf{D}_t$.

[5]No survival probability can be estimated for 1991 but is needed on the third step. In order not to lose all 1992 observations, I impute the survival probability in 1991 as the unweighted average of the 1989, 1990, and 1992 predictions for each firm.

Table 4: Observed and Predicted Survival

	Mean	S.dev.	Correlation coeff. Survv.[b]	Probit[b]	Logit[b]
Survival, overall[a]	.970	.172			
Survival, estimation sample[b]	.994	.075	1.000		
Probit prediction[b]	.973	.120	.249	1.000	
Logit prediction[b]	.973	.122	.256	.902	1.000

[a]68,984 observations
[b]48,697 observations

Table 4 shows that both the probit and the logit model predict slightly too few exits as compared to the data, and exhibit more dispersion. Financial variables of the firm such as its debt composition turn out to reduce the fit of the logit and probit models and are left out. Including the vector of market environment variables $\mathbf{D}_t$ improves the correlation between probabilities (between zero and one) and observed outcomes (either zero or one). The correlation coefficient increases from .211 to .249 in the case of probit and from .223 to .256 under logit. The logit model slightly outperforms probit in the estimation sample of all 27 sectors and is kept subsequently.

A third-order polynomial expansion approximates $g\left(P(\cdot), h(\cdot)\right)$ in equation (9) and gives rise to the estimation equation

$$\begin{aligned} z_{i,t+1} - \hat{\beta}_{0,i} - \hat{\beta}_{bl}\, l^{bl}_{i,t+1} - \hat{\beta}_{wh}\, l^{wh}_{i,t+1} - \hat{\beta}_{\mu}\, \mu^{f}_{i,t+1} - \hat{\beta}_{M}\, m_{i,t+1} \\ = \beta_{\kappa}\, \kappa^{f}_{i,t+1} + \beta_{K}\, k_{i,t+1} + \beta_{S}\, s_{i,t+1} + \sum_{m=0}^{3} \sum_{n=0}^{3-m} \beta_{m,n} (\hat{P})^{m} (\hat{h})^{n} + \eta_{i,t+1}. \end{aligned} \tag{15}$$

Non-linear least squares are applied, using the fixed-effects estimates as starting values.

Table 5 lists production function estimates for the five largest sectors in firm-year observations (among the total of 27 sectors). The extended Olley and Pakes (EOP) procedure is demanding on the data. The number of usable observations can be considerably less than initial observation counts (particularly striking are sectors 14 and 22). Including a multi-variate set of expectation proxies—individual investment, market environment variables, and their interactions—results in significant coefficients on a number of those proxies in several sectors.

Table 6 contrasts key estimates from the extended Olley and Pakes (EOP) procedure with fixed-effect regressions, an alternative estimation method under

Table 5: Production Function Estimates

	Machinery (08)	Wood & furniture (14)	Textiles (22)	Plant products (26)	Food & beverages (31)
Log blue-coll. empl.	.396	.426	.396	.347	.386
	(.025)	(.026)	(.025)	(.021)	(.029)
Log white-coll. empl.	.23	.156	.15	.219	.195
	(.018)	(.014)	(.018)	(.017)	(.016)
Log equipment	*.013*	.175	*.03*	.081	.066
	(.016)	(.019)	(.016)	(.018)	(.014)
Log structures	.077	.06	.079	.058	.039
	(.017)	(.016)	(.016)	(.023)	(.013)
Log intermediates	.228	.229	.322	.244	.211
	(.015)	(.013)	(.019)	(.013)	(.012)
Net equipment inv.	*1.00e-05*	*-.00003*	*6.46e-06*	*8.22e-06*	*5.68e-06*
	(1.00e-05)	(.00004)	(1.00e-05)	(.00003)	(.00002)
Net structures inv.	*-7.64e-06*	*4.33e-06*	*-7.89e-06*	*6.13e-06*	*.00002*
	(1.00e-05)	(.00002)	(5.73e-06)	(1.00e-05)	(1.00e-05)
Foreign market pen.	*-391.252*	*-529.533*	1008.876	*85.044*	-1945.13
	(713.367)	(306.53)	(419.31)	(305.721)	(547.761)
Nominal tariff	*-19.154*	*-50.555*	97.281	*14.023*	-193.01
	(74.215)	(30.249)	(41.34)	(30.431)	(54.776)
Log aggr. demand	307.473	137.578	289.411	*65.781*	*-115.13*
	(95.159)	(47.621)	(66.741)	(69.821)	(80.881)
Eqpm.inv. * For.pen.	*-2.47e-07*	*-1.29e-06*	*-2.46e-07*	*-8.12e-07*	*5.94e-08*
	(1.01e-06)	(1.63e-06)	(8.45e-07)	(6.88e-07)	(1.05e-06)
Eqpm.inv. * Tariff	*2.27e-08*	*-2.17e-07*	*1.73e-08*	*1.01e-07*	*7.08e-09*
	(1.04e-07)	(3.45e-07)	(5.90e-08)	(1.70e-07)	(1.19e-07)
Struct.inv. * For.pen.	*1.13e-07*	*-5.06e-07*	*-6.11e-07*	*-1.64e-08*	-7.71e-07
	(6.25e-07)	(6.51e-07)	(4.55e-07)	(4.10e-07)	(3.82e-07)
Struct.inv. * Tariff	*7.56e-08*	*3.75e-08*	*3.58e-08*	1.36e-07	*1.48e-08*
	(5.16e-08)	(1.85e-07)	(3.87e-08)	(6.78e-08)	(3.80e-08)
For. eqpm. share	*.073*	-.299	.138	-.243	*-.044*
	(.099)	(.071)	(.043)	(.101)	(.086)
For. intm. share	*.114*	*.262*	*-.532*	*-.223*	*-.129*
	(.575)	(.239)	(.277)	(.21)	(.268)
Obs.	2,695	2,835	3,260	2,764	3,432
Obs. step 1 (eq. 13)	2,528	598	609	2,382	2,622
Obs. step 3 (eq. 15)	1,890	470	290	1,808	1,991

Data: *Pesquisa Industrial Annual* 1986-1998. Standard errors from 200 bootstraps.
Not reported: Log age, real exchange rate, inflation rate, higher-order polynomial terms.

Table 6: Comparison of Production Function Estimates

	EOP		FE		OLS	
	Coef.	S.err.[a]	Coef.	S.err.	Coef.	S.err.
	(1)	(2)	(3)	(4)	(5)	(6)
(08) Machinery						
Log blue-coll. empl.	.396	.025	.439	.017	.243	.014
Log white-coll. empl.	.230	.018	.238	.016	.319	.014
Equipment	.013	.016	.013	.015	.069	.009
Structures	.077	.017	.077	.014	.053	.011
Log intermediates	.228	.015	.244	.010	.365	.010
(14) Wood and furniture						
Log blue-coll. empl.	.426	.026	.563	.018	.367	.015
Log white-coll. empl.	.156	.014	.165	.015	.216	.013
Equipment	.178	.019	.178	.015	.085	.010
Structures	.060	.016	.060	.015	.039	.010
Log intermediates	.229	.013	.232	.010	.335	.009
(22) Textiles						
Log blue-coll. empl.	.396	.025	.473	.015	.256	.012
Log white-coll. empl.	.150	.018	.177	.015	.209	.012
Equipment	.030	.016	.030	.013	.041	.008
Structures	.080	.016	.080	.012	.042	.009
Log intermediates	.322	.019	.311	.009	.457	.008
(26) Plant products						
Log blue-coll. empl.	.347	.021	.395	.018	.25	.015
Log white-coll. empl.	.219	.017	.238	.017	.243	.014
Equipment	.084	.018	.084	.016	.055	.011
Structures	.057	.023	.057	.015	.126	.012
Log intermediates	.244	.013	.230	.009	.385	.008
(31) Other food and beverages						
Log blue-coll. empl.	.386	.029	.490	.016	.273	.013
Log white-coll. empl.	.195	.016	.209	.013	.229	.011
Equipment	.068	.014	.068	.014	.085	.010
Structures	.038	.013	.038	.012	.081	.011
Log intermediates	.211	.012	.179	.008	.338	.008

[a] Estimates from 200 bootstraps

the behavioral assumptions but usually the most strikingly different estimator. Most importantly, capital coefficients on equipment and structures coincide for the EOP and the fixed-effects estimators (FE). When using the expectations proxy variables and firm-fixed effects on step 1 of EOP, the subsequent step 3 procedure of EOP confirms the initial capital coefficient estimates from the fixed-effects estimation (for the five select sectors, differences only occur past the third digit). This agreement between EOP and FE estimates seems to indicate that the expectations proxy variables to productivity largely capture the firm-specific time-variant effect that several prior studies detected.

Among the five select sectors, the OLS equipment coefficients appear to suffer from a negative bias in 2 out of five cases, with a significantly lower OLS coefficient than the EOP coefficient in 1 out of five cases (one-sided t tests). The OLS structures coefficients exhibit a negative bias in 3 out of five cases, with significantly lower OLS coefficients than the EOP coefficient in one case.[6] Contrary to the shorter Levinsohn and Petrin procedure, the complete algorithm of this section explicitly controls for survival and detects a negative bias in several OLS coefficients. Capital-rich firms are willing to bear worse productivity shocks and stay in business. This introduces a negative bias that may lie behind the low OLS capital coefficients in micro data.

Foreign market penetration might induce surviving firms to raise productivity in order to compete, suggesting a positive coefficient in an output regression on market penetration, whereas tariff protection would reduce the incentives to raise productivity, resulting in a negative coefficient. However, the coefficients on foreign market penetration and nominal tariffs do not exhibit a uniform pattern in table 5. Sector-specific production estimation implies that only time variation identifies these coefficients. Coefficient estimates on foreign input shares are partly significant, but unexpectedly negative in some sectors. The mean firm in those sectors seems to fail in putting the foreign inputs to a sufficiently productive use. Muendler (2004) conducts a more detailed analysis of these covariates.

The coefficients on aggregate demand in table 5 are positive and mostly significant, indicating a procyclical component in the output measure. This component can be related to productivity but may partly be due to varying markups. Section 1.2 discusses a partial treatment of potential time-invariant markups following Klette and Griliches (1996), and the following section 5 applies the treatment to firm-level productivity estimates. Section 6 discusses the relationship to markups in final-goods prices and to scale economies.

[6] The OLS equipment coefficients show a negative (significantly negative) bias in 13 (6) out of 27 sectors in total; and the OLS structures coefficients a negative (significantly negative) bias in 11 (3) out of 27 sectors in total.

In summary, the Olley and Pakes algorithm and the use of firm-level investments interacted with sector-level competition measures as proxies to productivity choice yield estimates that resemble or even coincide with fixed-effects estimates. So, competition measures joined by firm-level investment arguably remove the firm-specific time-variant effect that used to distort production function estimates. Moreover, while the shorter Levinsohn and Petrin algorithm in the previous section 3 had apparently detected surprising positive biases in OLS capital coefficients, the extended Olley and Pakes algorithm tends to find, and mitigate, a negative bias in OLS capital coefficients.

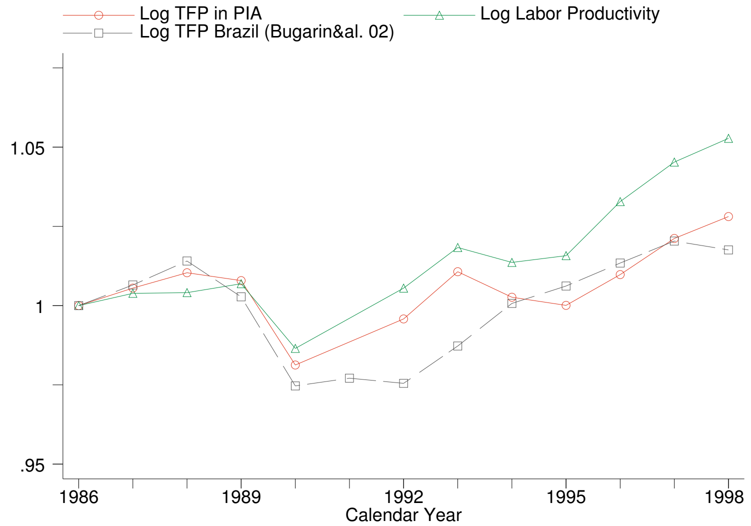
5 Inference of Firm-level Productivity Change

Given production function estimates under endogenous productivity and endogenous output price, the logarithm of total factor productivity at the firm level $\ln TFP_{i,t} = \beta_{0,i} + \nu\xi_{i,t} + \epsilon_{i,t}$ becomes

$$\begin{aligned} \alpha \ln TFP_{i,t} &= y_{i,t} - \widehat{(1-\alpha)(\bar{\theta}_t - \bar{p}_t)} \\ &\quad - \left(\hat{\beta}_{bl}\, l^{bl}_{i,t} + \hat{\beta}_{wh}\, l^{wh}_{i,t} + \hat{\beta}_K\, k_{i,t} + \hat{\beta}_S\, s_{i,t} + \hat{\beta}_M\, m_{i,t}\right), \end{aligned}$$

by (10), where $y_{i,t} = (p_{i,t} - \bar{p}_t) + z_{i,t}$ denotes the total of deflated sales and production for store. The term $(1-\alpha)(\bar{\theta}_t - \bar{p}_t)$ is the average firm-fixed effect $\overline{\beta_{0,i}}$ from production function estimates (13). It corrects for sector-specific and time-invariant demand-side effects that affect productivity estimates through price $p_{i,t}$ in $y_{i,t}$ (Klette and Griliches 1996, see section 1.2). Due to monopolistic competition, the time-invariant demand-side parameter α (where $-1/(1-\alpha)$ is price elasticity of demand) scales the firm-specific productivity level $\ln TFP_{i,t}$ up or down. This scaling parameter, however, does not impair the calculation of firm-specific or sector-wide productivity *changes*. So, no further treatments are needed to infer productivity change.

Since firm-fixed effects $\beta_{0,i} - \overline{\beta_{0,i}}$ beyond sector-wide effects $\overline{\beta_{0,i}}$ would not capture any of the time varying distortions from markups, quality or varieties but would remove firm-specific productivity advantages, I do not subtract firm-fixed effects from log TFP. Whether or not firm-fixed effects are removed, all time-varying price-related distortions to the productivity measure remain untreated. In particular, equation (16) implies that the sector-wide and firm-specific markup $(1/\alpha)$ lowers the firm-level productivity estimates. Moreover, the quality of output and the number of varieties that multi-product firms produce are unobserved. Both quality and variety increase the firm-fixed effect $\beta_{0,i}$ if they are specific to the firm and time-invariant (Melitz 2000). In this



Data: Firm-level productivity in 27 manufacturing sectors in *PIA* from EOP estimates, compared to Log *TFP* estimates by Bugarin, Ellery Jr., Gomes and Teixeira (2002).

Figure 5: **Log *TFP* and labor productivity in manufacturing**

regard, the present productivity measure enfolds quality. So, firm-fixed effects, beyond sector-wide effects, are a part of firm-level log *TFP*.

Figure 5 illustrates how *TFP* evolves in the aggregate of all 27 manufacturing sectors between 1986 and 1998. The year 1986 is re-based to unity for each sector so that any time-invariant demand-side scale effects due to monopolistic competition are removed.[7] Except for a larger drop during the recession in the late eighties and the subsequent recovery, changes are small in general. At its trough, log *TFP* drops to .981 in 1990, but recovers and reaches 1.028 by 1998, roughly a five-percent increase over 8 years. Bugarin et al. (2002) report similar, though more volatile aggregate *TFP* figures for Brazilian industry. Cavalcanti Ferreira and Rossi (2003) find no productivity drop during the 1988-90 recession and a more pronounced labor productivity increase dur-

[7] The underlying weighting scheme is output-based:

$$\ln TFP_t \equiv \sum_s \sum_{i \in \mathbb{S}_{s,t}} \theta_{s,t}\, \sigma_{i,t} \ln TFP_{i,t},$$

where the weights $\theta_{s,t}$ denote sector s' share of output in total output at time t, and $\sigma_{i,t}$ the share of firm i's output in sector s' output at time t. Double weighting makes productivity indices more comparable across sectors. Labor productivity is calculated as $\ln LP_{i,t} = \ln TFP_{i,t} + \hat{\beta}_K\, k_{i,t} + \hat{\beta}_S\, s_{i,t} + \hat{\beta}_M\, m_{i,t} - (1 - \hat{\beta}_{bl} - \hat{\beta}_{wh})(\ln(L^{bl}_{i,t} + L^{wh}_{i,t}))$.

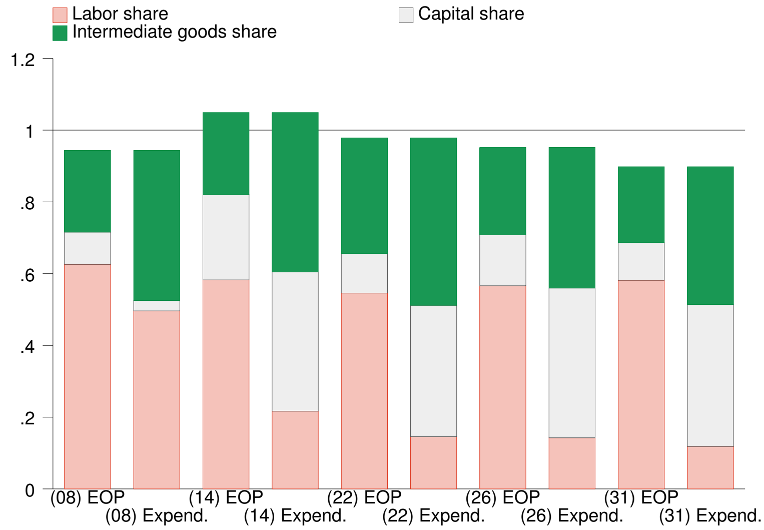
ing the 1990s. The present study is the first to employ an extensive firm-level sample. Most previous studies on Brazilian industry consider labor productivity. As figure 5 shows, labor productivity increases more strongly than *TFP* during the 1990s (from .986 to 1.053) because firms raise their capital stock.

Some potential sources of mismeasurement in productivity change remain. They affect the present firm-level estimates but production function estimation at higher aggregates would not necessarily mitigate them. First, if industry-wide markups erode over time—with α gradually approaching unity rather than being fixed as the parsimonious model suggests—, then the *TFP* measure will *increase too little* or *fall* over time (even though the factor α in front of $\ln TFP_{i,t}$ appears to indicate otherwise). The reason is that α remains unmeasured in the time-invariant production coefficient estimates and biases the average production coefficients in (10) downward because early years with lower α reduce the estimates. So, higher factor-input terms should be subtracted from output particularly in the earlier years than are removed in fact. This makes the $\alpha \cdot \ln TFP_{i,t}$ measure increase too little or fall over time. Second, a similar argument applies to economies of scale. If increasing returns are understated, as is likely, smaller factor-input terms are subtracted from output than should be removed. Productivity rises as output grows proportionally faster than inputs so that the removal of downward biased factor-input terms will make the *TFP* measure *increase too little.* On these accounts, the measured productivity change may understate Brazil's productivity advancement.

6 Open Issues

The size of the bars in figure 6 reflects the estimates of economies of scale under EOP (one pair of bars per sector). As is frequently the case in micro-data, the sums of factor coefficients exhibit, one exception notwithstanding, decreasing returns to scale (totals range from .90 in (31) food and beverages to 1.05 in (14) wood and furniture).

However, the correction for scale economies remains an open issue. As opposed to the coefficient estimates on log aggregate demand in Klette and Griliches (1996) for Norwegian manufacturing firms, where estimates ranged between zero and unity, expectation-proxy estimation in the present framework, with higher-order interactions, yields coefficient estimates orders of magnitude above unity. So, aggregate demand coefficient estimates imply that $1-\alpha > 1$, whereas the positive input coefficient estimates require that $\alpha > 0$. This contradictory finding refutes the validity of aggregate demand as a sufficient proxy to measure price elasticity. In the five select sectors, the coefficient on log aggregate demand is consistently above one hundred when significant.



Data: *Pesquisa Industrial Annual* 1986-1998
Expenditure shares: Intermediate goods expenditure per output; labor costs (including salaries, social contributions and benefits) and user costs of capital (including depreciation, financing costs, and pre-tax profits) in non-intermediate goods expenditures. Economies-of-scale estimate from sum of EOP coefficients.

Figure 6: **Factor shares from EOP estimates and crude expenditures**

A coefficient estimate for $(1-\alpha)$ of 300, for instance, would imply a price elasticity of demand $(-1/(1-\alpha))$ of -.003, if measured correctly. So, price increases would lead to hardly any demand reductions and manufacturers could wield substantial pricing power.[8] The magnitudes appear unreasonable and call for the development of a different scale-correction method. The theoretical model of endogenous efficiency choice suggests that firms' procyclical investments in productivity improvement are the likely reason for the high coefficient estimates on log aggregate demand.

Figure 6 also points to peculiarities in the composition of relative factor shares in firm-level expenditure and production. The surprising discrepancies raise several questions for further research. The left bar in each sector pair shows the EOP coefficient estimates, the right bar the expenditure shares (the height of the right bar is set equal to the sum of EOP coefficients). On average across sectors, the sum of (Cobb-Douglas) EOP capital coefficients is less than a quarter of the sum of labor coefficients. This is a low ratio but would not be substantially higher with OLS estimation even in sectors with a

[8] However, the markup $1/\alpha$ in the present theory model is not well defined for price elasticities of demand larger than -1 (smaller than 1 in absolute value).

positive bias in capital coefficients. While blue and white-collar labor coefficients in EOP estimation sum to roughly 60 percent in the select five sectors, the share of labor-related costs (salaries, social contributions and benefits) in total firm-level expenditures (excluding water and electricity) falls below 20 percent in three out of five sectors. On the other hand, expenditure shares of intermediate goods and user costs of capital (depreciation, financing costs, and pre-tax profits) as a share of total expenditure account for a substantially larger portion of factor incomes than production coefficients on intermediate goods and the sum of the equipment and structures coefficients would suggest. (The machinery sector (08) suffers considerable losses over the sample period; these losses account for the small share of capital in factor incomes in that sector.)

Several reasons, some specific to the Brazilian context, may lie behind these surprising disproportions. First, while production function coefficients are estimated at the sample mean, firm heterogeneity may distort expenditure shares away from marginal products of the mean firm. Second, gains from under-represented returns to scale likely accrue more to capital owners than to workers, boosting the expenditure share on capital beyond its marginal product. Third, real money-market interest rates of above forty percent are common in Brazil during the sampling period. If firms reduce their capital-output ratios less than proportionally (less than $\beta_K/(\beta_L+\beta_M)$ under Cobb-Douglas)—in expectation of more adequate future interest rates, for instance—then capital-cost expenditures exceed the marginal product of capital. Fourth, financing costs also accrue on capital that is not invested in fixed assets so that financial expenditure shares are naturally larger than production coefficients on capital. Finally, remaining measurement error in the capital stock series could bias the probability limits of the capital coefficients towards zero, whereas head counts of workers arguably suffer less measurement error. An investigation into the exact causes of the detected discrepancies between production coefficients and expenditure shares remains a task for future research.

7 Conclusion

Managements seek to streamline processes and improve efficiency, they invest in productivity-relevant assets and activities, and thus respond to individual market prospects. A large body of recent empirical evidence confirms that product-market competition tends to exert discipline on managers and to instill investment in process innovations (Tybout et al. 1991, Levinsohn 1993, Tybout and Westbrook 1995, Nickell 1996, Djankov and Hoekman 2000, Pavcnik 2002). This suggests that a superior proxy to productivity choice may be firm-level investment interacted with sector-level competition variables such as, for instance, foreign market penetration.

From this general insight derives an estimation framework. For simplicity, it builds on a q-theory model of investment in capital and productivity under convex adjustment costs. The model implies that firms set investment schedules so that capital and productivity rise or decay simultaneously. So, variables that characterize a firm's competitive environment, interacted with the firm's individual investment, are suitable proxies to endogenous productivity choice. Apart from the choice of proxies, the theoretical model gives rise to an estimation framework similar to Olley and Pakes (1996).

The new proxies resolve the empirical puzzle that fixed-effects estimators frequently and sharply disagree with all other estimators. This repeated finding suggests the presence of a persistent within-firm but time-varying shock that is correlated with inputs. Under the present framework, however, coefficient estimates for equipment and structures coincide with those from fixed-effects estimation. So, the untreated shock that troubled prior estimators appears to be the firm-level assessment of individual business prospects and the resulting firm-level efficiency response to the competitive environment.

Applied to a sample of medium-sized to large Brazilian manufacturing companies between 1986 and 1998, the proposed expectations proxies improve the precision of estimates and the convergence properties. Absent a correction for survival likelihoods in the shorter Levinsohn and Petrin (2003) procedure, both the expectations-proxy and the intermediate-inputs proxy would find capital and intermediate goods coefficients that are *lower* than OLS (a surprising positive bias, though consistent with aspects of the theory). However, when explicitly accounting for firms' survival likelihoods, the extended Olley and Pakes algorithm finds and mitigates a commonly expected negative bias in OLS capital coefficients for several sectors. Most importantly, the use of firm-level investments interacted with sector-level competition measures as proxies to productivity yield estimates that closely resemble fixed-effects estimates. So, competition measures joined by firm-level investment appear to remove the often suspected firm-specific time-variant effect that used to distort production function estimates. The procedure seems to be successful in removing two common biases that affect production coefficients in micro-data: A 'survivor bias', induced through exits that depend on firm-level productivity, and a 'transmission bias' that arises because physical investment is correlated with firm-level productivity.

These advances notwithstanding, open issues remain to resolve. Coefficient estimates on log sector-wide demand, a further competition proxy, are high and appear to capture firms' efficiency choice rather than an omitted price effect. This limits Klette and Griliches' (1996) proposed correction method for 'omitted price bias.' The 'omitted price bias' stems from the fact that price is unobserved in revenues but endogenous under imperfect competition so that a demand-side factor scales down production-function coefficients jointly and causes underestimated economies of scale. The lacking treatment of scale economies in the present framework may also lie behind unresolved discrepancies between input coefficient estimates and factor shares in firm-level expenditure. Gains from under-represented returns to scale likely accrue more to capital owners than to workers, boosting the expenditure share on capital beyond its marginal product. Moreover, firm heterogeneity may distort expenditure shares away from marginal products of the mean firm. Finally, changing but untreated markups may affect firm-level productivity estimates. Empirical investigations into the exact causes of the detected discrepancies between production coefficients and expenditure shares, and into time-varying markups, remain important tasks for future research.

Appendix

A Behavioral Framework

This appendix presents a behavioral framework, to incorporate the frequent empirical finding that efficiency choice and managerial efforts respond to market conditions. According implications for estimation under 'selection bias,' 'transmission bias,' and 'omitted price bias' are derived. Table 1 in the text provides an overview of the main ingredients and the implications of the model.

Firms invest in both capital goods and productivity-relevant assets. The model provides a production-side explanation why the bias in OLS capital coefficients may be positive. The model motivates a variant of Olley and Pakes' estimation procedure. The model implies that observations with non-positive investment need not be dropped from the sample. The model also implies that, rather than intermediate goods as in Levinsohn and Petrin (2003), investment interacted with sector-level competition variables is the most suitable productivity proxy. The model incorporates a partial Klette and Griliches' (1996) correction method. Optimality conditions are derived using principal-agent and q-theory and underly most estimation equations. Market clearing, on the other hand, is only needed for the derivation of the partial Klette and Griliches' (1996) correction method. Two testable implications of the proposed model are that the productivity level and the capital stock are positively correlated among survivors, and that productivity should be procyclical. Both implications are borne out in the present data.

A.1 Assumptions

Firms invest in two state variables, capital and efficiency-relevant assets. There are several flow variables. Besides investment, which moves the two state variables, firms employ labor and use intermediate goods.

The variable $\Omega_{i,t}$ is the total of a firm's tacit knowledge, organizational skills, and efficiency-relevant arrangements embodied in the production process. All of these factors contribute to a firms' *TFP* level. They are not transferrable from one firm to another but can be accumulated within a firm. They depreciate unless cultivated with investment $I^{\Omega}_{i,t+1}$. For simplicity, *TFP* is assumed to be

$$TFP_{i,t} = (\Omega_{i,t})^{\nu} \tag{A.1}$$

for some coefficient $\nu > 0$. As opposed to physical capital accumulation, there is a stochastic factor $\tilde{x}_{i,t}$ to the evolution of organizational knowledge:

$$\Omega_{i,t} = \left[\Omega_{i,t-1}(1-\delta^{\Omega}) + I^{\Omega}_{i,t}\right] \cdot \tilde{x}_{i,t}. \tag{A.2}$$

The parameter δ^{Ω} expresses the depreciation rate of organizational knowledge. Productivity choice is an imperfect substitute for physical capital because $(\Omega_{i,t})^{\nu}$ will enter the production function separately and a firm cannot anticipate the realization $x_{i,t}$. The stochastic factor $\tilde{x}_{i,t}$ captures a firm's efficiency and is assumed to be uncorrelated with its past realizations and factor inputs—similar to the spirit of Olley and Pakes' (1996) model. However, the efforts of a firm's management to improve efficiency and make better use of organizational skills can affect the distribution of $\tilde{x}_{i,t}$ favorably (more on this in section A.3).

Consider a market with monopolistic competition. Each firm manufactures one variety of a good. Consumers have income Y_t and preferences as in a standard model for intraindustry trade: $u(Z_1, ...Z_N; C) = (\theta/\alpha)\ln(\sum_{n=1}^{N}(Z_n)^{\alpha}) + (1-\theta)\ln C$. There are N varieties of good Z. Under this utility, price elasticity of demand for a modern good i is approximately $-1/(1-\alpha)$ and results in a markup factor of $1/\alpha$ over marginal cost.[9] With a price index $\bar{P}_t \equiv [\sum_{n=1}^{N} P_{n,t}^{-\alpha/(1-\alpha)}]^{-(1-\alpha)/\alpha}$, similar to a statistical bureau's price index, demand for firm i's good can be stated as

$$D_{i,t} = \frac{\Theta_t}{\bar{P}_t} \cdot \left(\frac{P_{i,t}}{\bar{P}_t}\right)^{-\frac{1}{1-\alpha}}, \tag{A.3}$$

where Θ_t is the disposable income that domestic consumers spend on goods Z, including imports. This will be a key relationship for the correction of endogenous price in sales (Klette and Griliches 1996).

To see more clearly how foreign competition affects demand, suppose that domestic varieties of a good sell at about the same price. However, there is a possibly different world market price P_t^f for foreign varieties that compete with firm i's good. Then, domestic demand for a domestic manufacturer i's variety is[10]

$$D_{i,t} = \frac{1}{1 + \frac{N_t^{for}}{N_t^{dom}}\left(\frac{P_{i,t}}{\varepsilon_t P_t^f(1+\tau_t)}\right)^{\frac{\alpha}{1-\alpha}}} \frac{\Theta_t}{N_t^{dom}} \frac{1}{P_{i,t}}, \tag{A.4}$$

where ε_t is the nominal exchange rate, and τ_t the nominal tariff in the market of firm i. N_t^{dom} and N_t^{for} denote the number of domestic and foreign varieties, respectively. Their ratio is a measure of foreign market penetration. Demand for a domestic firm's variety increases when there are relatively fewer foreign competitors, or when foreign price is higher, tariffs are higher, or the exchange rate is more favorable—as one would expect.

[9] The precise price elasticity of demand is

$$\varepsilon_{d_{i,t},p_{i,t}} = -\frac{1}{1-\alpha}\left[1 - \alpha\left(\frac{\bar{P}_t}{p_{i,t}}\right)^{\frac{\alpha}{1-\alpha}}\right]$$

giving rise to a markup $p^{i,t} \simeq \frac{1}{\alpha} MC_{i,t}$ over marginal cost MC.

[10] See Muendler (2002, equation (2.27)).

A.2 A firm's price, factor, and investment choice

Boone (2000) shows conditions when more competition provides incentives to innovate products or processes. The present model is more modest. Based on textbooks theories of monopolistic competition and investment under convex adjustment costs, its main objective is to provide an estimation framework that is consistent with endogenous productivity choice and that can be related to previously introduced estimation procedures by Olley and Pakes (1996), Klette and Griliches (1996), and Levinsohn and Petrin (2003).

A monopolist in the market for good Z sets price and chooses the variable factors in every period t, given his capital stock and TFP. The production technology for variety i of good Z is assumed to be Cobb-Douglas:

$$Z_{i,t} = (\Omega_{i,t})^{\nu} (K_{i,t})^{1-\beta} (L_{i,t} - L_0)^{\beta}, \tag{A.5}$$

where $(\Omega_{i,t})^{\nu}$ is TFP. $L_{i,t}$ denotes employment, the only variable factor for now. L_0 is a fixed labor input needed in every period to keep the firm in operation. It gives rise to monopolistic competition in equilibrium.

Consider a firm's intertemporal choice of its capital stock and organizational knowledge, and whether to continue in business or to shutdown. If the firm exits, it receives a payment Φ_t for its remaining assets. Tomorrow's capital stock is certain, $K_{i,t+1} = K_{i,t}(1-\delta^K) + I^K_{i,t+1}$, whereas tomorrow's organizational knowledge is partly random and given by (A.2). Investments $I^K_{i,t+1}$ and $I^{\Omega}_{i,t+1}$ are decided at the end of period t, result in an immediate cash outflow but become affective only in period t+1. Adjustment costs for organizational knowledge, $\psi^{\Omega}(I^{\Omega}_{i,t+1})^2/(2\Omega_{i,t})$, are quadratic as in a textbook model of Tobin's q. Similarly, adjustment costs for the capital stock are $\psi^K(I^K_{i,t+1})^2/(2K_{i,t})$. Then the Bellman equation becomes

$$\begin{aligned} V(\Omega_{i,t}, K_{i,t}) \;=\; \max \Bigg[\Phi_t, \sup_{I^{\Omega}_{i,t+1}, I^K_{i,t+1}, L_{i,t}} & P^*(Z_{i,t}, \mathbf{D}_t)\, Z_{i,t} - w_t L_{i,t} - I^{\Omega}_{i,t+1} - I^K_{i,t+1} \\ & - \frac{\psi^{\Omega}}{2} \frac{(I^{\Omega}_{i,t+1})^2}{\Omega_{i,t}} - \frac{\psi^K}{2} \frac{(I^K_{i,t+1})^2}{K_{i,t}} + \frac{1}{R} \mathbb{E}\left[V(\Omega_{i,t+1}, K_{i,t+1}) \,|\mathcal{F}_{i,t} \right] \Bigg] \end{aligned} \tag{A.6}$$

where $R \equiv 1 + r$ is the real interest factor and $\mathcal{F}_{i,t}$ a firm's information set at time t. General market conditions, such as foreign market penetration, enter the decision through their effect on price. Each monopolist takes into account that higher supply depresses price given the demand schedule (A.4). So, a monopolist sees price as a function $P^*(Z_{i,t}, \mathbf{D}_t)$, where $\mathbf{D}_t \equiv (N^{for}_t/N^{dom}_t, \varepsilon_t, P^f_t, \tau_t; \Theta_t)$ stands for the vector of current market conditions that firm i faces. Price elasticity of demand $-1/(1-\alpha)$ is constant, however, and independent of $\mathbf{D}_t$.

First, consider the case of a firm that continues in business. Tobin's q's for organizational knowledge and physical capital can be defined as

$$q^{\Omega}_{i,t} \equiv \mathbb{E}_t\left[\frac{1}{R}\frac{\partial V(\Omega_{i,t+1},K_{i,t+1})}{\partial \Omega_{i,t+1}}\cdot x_{i,t+1}\right] \text{ and } q^{K}_{i,t} \equiv \mathbb{E}_t\left[\frac{1}{R}\frac{\partial V(\Omega_{i,t+1},K_{i,t+1})}{\partial K_{i,t+1}}\right]. \tag{A.7}$$

Then, the first-order conditions for the Bellman equation (A.6) imply that

$$q^{\Omega}_{i,t} = 1+\psi^{\Omega}\frac{I^{\Omega}_{i,t+1}}{\Omega_{i,t}}, \quad q^{K}_{i,t} = 1+\psi^{K}\frac{I^{K}_{i,t+1}}{K_{i,t}}, \quad \text{and} \quad L_t = L_0+\frac{\alpha\beta}{w_t}P^*(Z_{i,t},\mathbf{D}_t)Z_{i,t}. \tag{A.8}$$

Differentiating the value function with respect to the current state variable $\Omega_{i,t}$ and leading it by one period, one finds

$$R\, q^{\Omega}_{i,t} = \alpha\nu\mathbb{E}_t\left[\frac{P^*(\cdot)_{t+1}Z_{i,t+1}}{\Omega_{i,t+1}}\right] + \mathbb{E}_t\left[\frac{\psi^{\Omega}}{2}\frac{(I^{\Omega}_{i,t+2})^2}{(\Omega_{i,t+1})^2}\right] + (1-\delta^{\Omega})\,\mathbb{E}_t\left[q^{\Omega}_{i,t+1}\right] \tag{A.9}$$

by (A.7) and the envelope theorem. An according condition applies to Tobin's q for physical capital.

So, under the usual regularity (no bubble) conditions,

$$q^{\Omega}_{i,t} = \frac{1}{1-\delta^{\Omega}}\sum_{s=t+1}^{\infty}\left(\frac{1-\delta^{\Omega}}{R}\right)^{s-t}\mathbb{E}_t\left[\frac{\nu}{\Omega_{i,s}}\alpha P^*(Z_{i,s},\mathbf{D}_s)\,Z_{i,s}+\frac{\psi^{\Omega}}{2}\frac{(I^{\Omega}_{i,s+1})^2}{(\Omega_{i,s})^2}\right] \tag{A.10}$$

and

$$q^{K}_{i,t} = \frac{1}{1-\delta^{K}}\sum_{s=t+1}^{\infty}\left(\frac{1-\delta^{K}}{R}\right)^{s-t}\mathbb{E}_t\left[\frac{1-\beta}{K_{i,s}}\alpha P^*(Z_{i,s},\mathbf{D}_s)\,Z_{i,s}+\frac{\psi^{K}}{2}\frac{(I^{K}_{i,s+1})^2}{(K_{i,s})^2}\right]. \tag{A.11}$$

A firm is uncertain about the realization of both future *TFP* and market conditions. The two terms in the expectations operator reflect the value of the respective state variable given market prospects $\alpha P^*(Z_{i,s},\mathbf{D}_s)\,Z_{i,s}$ and savings in future adjustment costs $(I^{K}_{i,s+1})^2/(K_{i,s})^2$. So, market conditions affect the value of both state variables in a very similar way.

As a consequence, the model implies that a firm's capital stock and organizational knowledge are correlated from a researcher's perspective. By (A.8) and (A.2),

$$\Omega_{i,t+1} = x_{i,t+1}\cdot\Omega_{i,t}\left[\frac{q^{\Omega}_{i,t}-1}{\psi^{\Omega}}+(1-\delta^{\Omega})\right]. \tag{A.12}$$

An according condition holds for $K_{i,t}$. So, for the researcher, the correlation between *TFP* and capital becomes

$$\mathbb{C}ov_t\left(\Omega_{i,t+1},K_{i,t+1}\,|\Omega_{i,t},K_{i,t}\right) = \frac{\Omega_{i,t}K_{i,t}}{\psi^{\Omega}\psi^{K}}\,\mathbb{C}ov_t\left(q^{\Omega}_{i,t},\,q^{K}_{i,t}\right). \tag{A.13}$$

For the firm, $q^{\Omega}_{i,t}$ and $q^{K}_{i,t}$ are certain, given its information. The correlation is zero from its point of view. The researcher, on the other hand, does not know a firm's information set. Therefore, the data will exhibit a correlation between capital and *TFP*. The correlation is likely to be positive since future revenues affect both $q^{\Omega}_{i,t}$ and $q^{K}_{i,t}$ positively. Concretely, by (A.10) and (A.11),

$$q^{\Omega}_{i,t} = \rho_{i,t}(\mathbf{D}^e_t) \cdot q^{K}_{i,t} \tag{A.14}$$

where

$$\rho_{i,t}(\mathbf{D}^e_t) \equiv \frac{\sum_{s=t}^{\infty} \left(\frac{1-\delta^{\Omega}}{R}\right)^{s-t} \mathbb{E}_t \left[\frac{\nu}{\Omega_{i,s+1}} \alpha P^*(Z_{i,s+1}, \mathbf{D}_{s+1})\, Z_{i,s+1} + \frac{\psi^{\Omega}}{2} \frac{(I^{\Omega}_{i,s+2})^2}{(\Omega_{i,s+1})^2} \right]}{\sum_{s=t}^{\infty} \left(\frac{1-\delta^{K}}{R}\right)^{s-t} \mathbb{E}_t \left[\frac{1-\beta}{K_{i,s+1}} \alpha P^*(Z_{i,s+1}, \mathbf{D}_{s+1})\, Z_{i,s+1} + \frac{\psi^{K}}{2} \frac{(I^{K}_{i,s+2})^2}{(K_{i,s+1})^2} \right]} > 0$$

conditional on survival. $\mathbf{D}^e_t \equiv \mathbf{E}_t[\{\mathbf{D}'_s\}_{s=t,\ldots,\infty}]'$ is the vector of current and future market conditions as expected at time t. A positive bias in OLS capital coefficients is frequently found in micro-data, refuting prior models that cannot account for this possibility.[11]

However, since there is exit from the sample, the correlation in (A.13) does not give the complete picture. In general, the shutdown rule for a firm depends on the firm's state variables and its information about revenue prospects. Since the value function is increasing in both state variables, there are lower threshold levels for the states below which a firm exits, given market prospects. Alternatively, the shutdown rule can be written as a function of the realization of the *TFP* innovation. After observing the realization of $x_{i,t}$, a firm decides whether or not it prefers to exit. Then,

$$\chi_{i,t+1} = \begin{cases} 0 & \text{if } x_{i,t} < \underline{x}(\Omega_{i,t-1}, I^{\Omega}_{i,t}; K_{i,t}, \mathbf{D}_t) \\ 1 & \text{else} \end{cases}, \tag{A.15}$$

where $\chi_{i,t+1} = 0$ means that firm i chooses to shutdown at the end of period t. If the value of current and discounted future profits falls short of the outside value Φ_t, the firm has no incentive to produce in the current or any future period. Since the value function (A.6) is strictly increasing in the capital stock,[12] the threshold level

[11] It is sometimes argued that a positive productivity shock may push demand for a firm's good more than proportionally and thus capital input, giving rise to a positive correlation through demand rather than production effects. In a model of the present structure but with productivity beyond a firm's control, an exogenous productivity shock translates one to one into an output change with no effect on input choice. Very specific assumptions on demand elasticity could allow a positive productivity shock to cause a more than proportional output increase and higher capital input. But *temporary* productivity shocks hardly affect capital input even under such strong assumptions.

[12] $\partial V(\cdot)/\partial K_{i,t} = \alpha(1-\beta)P^*(\cdot)_t Z_{i,t}/K_{i,t} + (1-\delta^K)q^K_{i,t} + \psi^K (I^K_{i,t+1})^2/(2K_{i,t}) > 0$. Estimates of exit probabilities from the second stage of the estimation algorithm confirm that capital-rich firms are less likely to exit.

$\underline{x}(\cdot)$ is strictly decreasing in $K_{i,t}$. A capital-rich firm is willing to bear lower *TFP* levels and still continues in business.

As Olley and Pakes (1996) point out, this introduces a negative correlation between the capital stock of survivors and the expected *TFP* level. Call the probability that a firm survives

$$Pr(\chi_{i,t+1} = 1 | \Omega_{i,t}, I^{\Omega}_{i,t+1}; K_{i,t+1}, \mathbf{D}_{t+1}) = P(\Omega_{i,t}, I^{\Omega}_{i,t+1}; K_{i,t+1}, \mathbf{D}_{t+1}). \qquad \text{(A.16)}$$

Then by (A.2),

$$\mathbf{E}[\Omega_{i,t+1} | \chi_{i,t+1} = 1] = \left[(1-\delta^{\Omega})\Omega_{i,t} + I^{\Omega}_{i,t+1}\right] \int_{\underline{x}(\cdot)} x_{i,t+1} \frac{f\left(x_{i,t+1}\right)}{P(\cdot)} \, dx_{i,t+1} \qquad \text{(A.17)}$$

for the researcher. At the lower bound on $x_{i,t+1}$, $\underline{x}(\Omega_{i,t}, I^{\Omega}_{i,t+1}; K_{i,t+1}, \mathbf{D}_{t+1})$, the firm is indifferent between staying in business and exiting. The bound strictly decreases in the capital stock $K_{i,t+1}$. Thus, the value of the integral will be the lower the higher the capital stock happens to be. In the data, a negative relation between capital and the expected *TFP* level is likely to result. It is not clear *a priori* whether a positive correlation from (A.13) would outweigh the negative bias from (A.17) or not. The present data detect positive biases in OLS capital coefficients for some sectors, and negative biases for others. In general, a negative bias in the frequently surprisingly low OLS capital coefficients is suspected.

A.3 Competition and a manager's efficiency choice

Product-market competition can induce managers to resolve agency problems and to remove managerial slack. Hermalin (1992) and Schmidt (1997) present theoretical circumstances when increasing competition forces firms to reduce agency problems and managerial slack. Though lacking the completeness of Hermalin (1992) and Schmidt (1997), a slight extension of the present model can incorporate these insights and help clarify further implications for productivity estimation.

A firm's investment in organizational skills $I^{\Omega}_{i,t+1}$ is observable to the firm's owner through cash flows. Similarly, $\Omega_{i,t}$ can be inferred from output. However, the manager's efforts in employing these organizational skills are not known. Successful efforts affect the distribution of the productivity shock $\tilde{x}_{i,t}$ in (A.2) favorably. In other words, efficiency improving investments are only successful if the management subsequently makes good use of the changes. This gives rise to moral hazard. Suppose that a manager can either choose high efforts or low efforts ($E_{i,t} \in \{e^H_{i,t}, e^L_{i,t}\}$) and that the distribution of $x_{i,t+1}|e^H_{i,t}$ stochastically dominates the distribution $x_{i,t+1}|e^L_{i,t}$.[13] Under the assumption that efforts only affect next year's productivity $x_{i,t+1} \sim f(x_{i,t+1}|E_{i,t})$, it is easy to see that the firm's owner bases the optimal

[13]Second-order dominance is assumed for $\nu < 1$. A mean-preserving spread leaves the firm-fixed effect $\beta_{0,i}$ unchanged.

(end-of-year) remuneration $w(\cdot)$ on the observation of $x_{i,t+1}$. The owner maximizes $V(\Omega_{i,t}, K_{i,t}) - (1/R)\mathbb{E}\left[w(x_{i,t+1})\right]$ given the risk averse manager's participation constraint $\mathbb{E}\left[u\left(w(x_{i,t+1})\right)\right] - E_{i,t} \geq \underline{u}$ and the manager's optimality condition

$$\int_{\underline{x}} u\left(w(x_{i,t+1})\right) \frac{f(x_{i,t+1}|e^H_{i,t})}{1 - F(\underline{x}|e^H_{i,t})} \, \mathrm{d}x_{i,t+1} - e^H_{i,t} \geq$$

$$\geq \int_{\underline{x}} u\left(w(x_{i,t+1})\right) \frac{f(x_{i,t+1}|e^L_{i,t})}{1 - F(\underline{x}|e^L_{i,t})} \, \mathrm{d}x_{i,t+1} - e^L_{i,t}. \tag{A.18}$$

It is straight forward to use the principal's first-order conditions and show that the optimal remuneration for the manager is strictly increasing in $x_{i,t+1}$ if and only if the likelihood ratio $f(x_{i,t+1}|e^H_{i,t})/f(x_{i,t+1}|e^L_{i,t})$ is strictly increasing in $x_{i,t+1}$. Suppose this is the case.

Fiercer competition raises $\underline{x}(\cdot; \mathbf{D}_{t+1})$ and firms go out of business more frequently. Hermalin (1992) and Schmidt (1997) show that high-effort contracts can but need not become easier to institute under fiercer competition. A similar ambiguity arises here but for different reasons. Note that the likelihood ratio is increasing in $x_{i,t+1}$ and hence in $\underline{x}$, but the ratio $(1-F(\underline{x}|e^H_{i,t})/(1-F(\underline{x}|e^L_{i,t})$ is also increasing in $\underline{x}$. Together, these facts can but need not make the left-hand side in (A.18) grow larger relative to the right-hand side under fiercer competition and may facilitate the institution of high-effort contracts. Irrespective of whether competition has a positive or negative effect on efficiency, productivity estimation can account for it by controlling for the competitive conditions in which a firm operates.

B The *Pesquisa Industrial Anual* Sample

The Brazilian statistical bureau (*IBGE*) conducts an annual survey of mining and manufacturing firms, called *Pesquisa Industrial Anual* (*PIA*). It comprises a sample of formally established, medium-sized to large Brazilian firms for the years 1986 to 1990, 1992 to 1995, and 1996 to the present.Mining is disregarded in this paper.

Muendler (2003) documents the construction of an unbalanced panel data set from *PIA* in detail—including the establishment of longitudinal relations between firms (such as entry, creation, exit, and mergers or acquisitions), consistency adjustments for economic variables due to questionnaire changes, price deflation of the economic variables, and the derivation of consistent capital stock series. This appendix merely summarizes the resulting data characteristics.

A firm qualifies for *PIA* if at least half of its revenues stem from manufacturing activity and if it is formally registered with the Brazilian tax authorities. In 1986, the initial *PIA* sample was constructed from three layers: (1) A non-random sample of the largest Brazilian manufacturers with output corresponding to at least 200 million Reais in 1995 (around 200 million US dollars in 1995). There were roughly

800 of them. (2) A random sample among medium-sized firms whose annual output in 1985 exceeded a value corresponding to R$ 100,000 in 1995 (around USD 100,000 in 1995). More than 6,900 firms made it into *PIA* this way. (3) A non-random selection of newly founded firms. *PIA* only included new firms that surpassed an annual average employment level of at least 100 persons. The inclusion process ended in 1993, however. Until then, around 1,800 firms were identified in this manner.

Departing from its initial 1986 sample, *PIA* identifies more than 9,500 active firms over the years. A firm that ever enters *PIA* through one of the selection criteria remains in the sample unless it is legally extinct. Moreover, if an existing firm in *PIA* reports the creation of a new firm as a subsidiary or spin-off, or a merger, this new firm enters *PIA* too. No sample was taken in 1991 due to a federal austerity program. The sampling method changed in 1996, and no capital stock figures are reported since. Therefore, the dataset of this paper only embraces firms after 1995 that were present in *PIA* earlier or that were longitudinally related to an earlier firm. Their capital stock is inferred with a perpetual inventory method. Following the change in sampling, there is a drop in the sample in 1996. Tests at various stages of the estimation prove it to be exogenous. Table 7 documents sample exit and sample attrition for the five largest sectors in *PIA*, on which most of the present analysis is based.

Output and domestic inputs are deflated with sector-specific price indices (constructed on the basis of Brazilian wholesale price indices and input-output matrices). Capital stock figures and investments are deflated with economy-wide price indices (constructed on the basis of Brazilian wholesale price indices and economy-wide capital formation vectors). Two steps are used to deflate foreign equipment acquisitions and foreign intermediate inputs. First, sector-specific series of import-weighted foreign producer prices, adjusted for nominal exchange rate fluctuations relative to the US-Dollar, are applied. Then, (investment-weighted) nominal tariffs on foreign machinery and (sector-specific input-weighted) nominal tariffs on intermediates are removed from equipment acquisitions and intermediate inputs.

To check for sensitivity, the data were deflated with three different price indices. The sector-specific wholesale price index *IPA-OG* underlies all results in this paper. Another sector-specific wholesale price index, *IPA-DI* (excluding imports), and the economy-wide price index *IGP-DI* (a combined wholesale and consumer price index) do not yield substantially different results. There is no producer price index for Brazil.

The overall capital stock is inferred under a perpetual inventory method that controls for changes to accounting law in 1991. Both investments and book values of capital goods are reported in *PIA* until 1995. Investments are assumed to become productive parts of the capital stock within the year of their reporting. They are used to infer typical depreciation rates through regression analysis. Foreign equipment levels are inferred from foreign equipment acquisitions and overall retirements. The structures part in total capital includes rented capital goods. These stocks of rented capital goods are inferred from reported rental rates, which are taken to equal the

Table 7: SAMPLE EXIT AND ATTRITION IN LARGEST FIVE SECTORS

	Observations	Survivors through 1998
	(1)	(2)
1986	1,945	685
1987	1,966	692
1988	2,365	730
1989	2,373	742
1990	2,313	747
1992	1,889	791
1993	1,838	817
1994	1,753	841
1995	1,653	854
1996	1,186	955
1997	1,150	989
Observations	21,465	
Firm panels	2,942	

Data: *Pesquisa Industrial Annual* 1986-1998. Sectors: (08) *Machinery*, (14) *Wood and furniture*, (22) *Textiles*, (26) *Plant products*, (31) *Other food and beverages.*

(time-varying) user cost of capital. Consistency adjustments are made under the perpetual inventory method when stock changes are observed that differ from net investments (different deflators can cause this). Usually, simple averages are used. Since sector-wide depreciation rates are applied, the resulting capital stock series for 1986-1998 are smoother across firms and over time than the raw series.

Sector classifications in *PIA* would allow for the estimation of production functions at a level that corresponds to three *ISIC rev. 3* digits (*nível 100*). However, large firms in *PIA* are likely to offer product ranges beyond narrowly defined sector limits. Data at more aggregate levels also provide more variation in the cross section because market penetration and tariff series then become available for two or more subsectors within several sectors. Moreover, switching from the three to the two-digit level increases the number of observations for productivity estimation considerably. So, estimations are carried out at the *ISIC rev. 3* two-digit level (*nível 50*).

References

Blundell, Richard and Stephen R. Bond, "GMM Estimation with Persistent Panel Data: An Application to Production Functions," *Econometric Reviews*, 2000, *19* (3), 321–40.

Boone, Jan, "Competitive Pressure: The Effects on Investments in Product and Process Innovation," *RAND Journal of Economics*, Autumn 2000, *31* (3), 549–69.

Bugarin, Mirta S., Roberto Ellery Jr., Victor Gomes, and Arilton Teixeira, "The Brazilian Depression of the 1980s and 1990s," August 2002. IPEA-DF (Instituto de Pesquisa Econômica Aplicada), Brasília, Mimeograph.

Cavalcanti Ferreira, Pedro and José Luis Rossi, "New Evidence from Brazil on Trade Liberalization and Productivity Growth," *International Economic Review*, November 2003, *44* (4), 1383–1405.

Djankov, Simeon and Bernard Hoekman, "Market Discipline and Corporate Efficiency: Evidence from Bulgaria," *Canadian Journal of Economics*, February 2000, *33* (1), 190–212.

Ericson, Richard and Ariel Pakes, "Markov-Perfect Industry Dynamics: A Framework for Empirical Work," *Review of Economic Studies*, January 1995, *62* (1), 53–82.

Griliches, Zvi and Jacques Mairesse, "Production Functions: The Search for Identification," in Steinar Strom, ed., *Econometrics and economic theory in the twentieth century: The Ragnar Frisch Centennial Symposium*, Cambridge, New York and Melbourne: Cambridge University Press, 1998, pp. 169–203.

Harrison, Ann E., "Productivity, Imperfect Competition and Trade Reform: Theory and Evidence," *Journal of International Economics*, February 1994, *36* (1-2), 53–73.

Hermalin, Benjamin E., "The Effects of Competition on Executive Behavior," *RAND Journal of Economics*, Autumn 1992, *23* (3), 350–65.

Klette, Tor Jakob and Zvi Griliches, "The Inconsistency of Common Scale Estimators When Output Prices Are Unobserved and Endogenous," *Journal of Applied Econometrics*, July 1996, *11* (4), 343–61.

Levinsohn, James, "Testing the Imports-as-Market-Discipline Hypothesis," *Journal of International Economics*, August 1993, *35* (1-2), 1–22.

—— **and Amil Petrin**, "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies*, April 2003, *70* (2), 317–41.

Mairesse, Jacques and Bronwyn H. Hall, "La productivité de la recherche et developpement des entreprises industrielles aux Etats-Unis et en France. Une exploration des biais de simultanité par la méthode des moments généralisés," *Economie et Prévision*, 1996, *126*, 91–110.

Marschak, Jacob and William H. Jr. Andrews, "Random Simultaneous Equations and the Theory of Production," *Econometrica*, July-October 1944, *12* (3/4), 143–205.

Melitz, Marc J., "Estimating Firm-level Productivity in Differentiated Product Industries," December 2000. Harvard University, Mimeograph.

Muendler, Marc-Andreas, "Essays on International Trade, Growth and Finance." PhD dissertation, University of California, Berkeley May 2002.

____, "The Database *Pesquisa Industrial Anual* 1986-2001: A Detective's Report," November 2003. Instituto Brasileiro de Geografia e Estatística, Rio de Janeiro, Mimeograph (*econ.ucsd.edu/muendler/brazil*).

____, "Trade, Technology, and Productivity: A Study of Brazilian Manufacturers, 1986-1998," February 2004. University of California, San Diego, Mimeograph.

Nickell, Stephen J., "Competition and Corporate Performance," *Journal of Political Economy*, August 1996, *104* (4), 724–46.

Olley, G. Steven and Ariel Pakes, "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, November 1996, *64* (6), 1263–97.

Pakes, Ariel, "Dynamic Structural Models: Problems and Prospects. Mixed Continuous Discrete Controls and Market Interactions," in Christopher Sims, ed., *Advances in Econometrics, Sixth World Congree*, Cambridge: Cambridge University Press, 1996, pp. 171–259.

Pavcnik, Nina, "Trade Liberalization, Exit, and Productivity Improvement: Evidence from Chilean Plants," *Review of Economic Studies*, January 2002, *69* (1), 245–76.

Schmidt, Klaus M., "Managerial Incentives and Product Market Competition," *Review of Economic Studies*, April 1997, *64* (2), 191–213.

Tybout, James, Jaime de Melo, and Vittorio Corbo, "The Effects of Trade Reforms on Scale and Technical Efficiency: New Evidence from Chile," *Journal of International Economics*, November 1991, *31* (3-4), 231–50.

Tybout, James R. and M. Daniel Westbrook, "Trade Liberalization and the Dimensions of Efficiency Change in Mexican Manufacturing Industries," *Journal of International Economics*, August 1995, *39* (1-2), 53–78.