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Jeremy T. Fox and Valérie Smeets

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Do Input Quality and Structural Productivity Estimates Drive Measured Differences in Firm Productivity?

Jeremy T. Fox & Valérie Smeets*
University of Chicago
Universidad Carlos III & CCP

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Abstract

Firms in the same industry can differ in measured total factor productivity (TFP) by multiples of 3. Griliches (1957) suggests one explanation: the quality of inputs differs across firms. Labor inputs are traditionally measured only as the number of workers. We investigate whether adjusting for the quality of labor inputs substantially decreases measured TFP dispersion. We add labor market history variables such as experience and firm and industry tenure, as well as general human capital measures such as schooling and sex. We also investigate whether an innovative structural estimator for productivity due to Olley and Pakes (1996) substantially decreases measured residual TFP. Combining labor quality and structural estimates of productivity, the one standard deviation difference in residual TFPs in manufacturing drops from 0.70 to 0.67 multiples. Neither the structural productivity measure nor detailed input quality measures explain the very large measured residual TFP dispersion, despite statistically precise coefficient estimates.

JEL codes: D24, L23, M11
Keywords: production function estimation, total factor productivity, input quality, structural estimates of productivity

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1 Introduction

Differences in output across firms can be decomposed into differences in measured inputs and differences in residuals. The literature typically estimates the Cobb-Douglas production function

$$y = \beta_0 + \beta_l l + \beta_k k + e, \tag{1}$$

where y is the log of value added, l is the log of the number of workers, and k is the log of the dollar value of physical capital. β_l and β_k are the input elasticities of labor and capital. Between two firms with the same inputs l and k, the firm with the higher output y is said to have a higher measured total factor productivity (TFP), which is $\exp(\beta_0 + e)$ above.

Measured differences in productivity across plants in the same industry can be large. Bartelsman and Doms (2000) survey the literature and find many instances where the highest productivity firm has more than twice the measured productivity of the lowest productivity firm. Also, Dhrymes (1995) studies American manufacturing firms and finds that the ratio of TFP of plants in the ninth decile to the TFP of plans in the second decile is 2.75 in 1987. We find that the standard deviation of log TFP is 0.54 in manufacturing, in Denmark. The TFP level of two standard deviation differences is $\exp(2 \cdot 0.54) - 1 = 1.94$ multiples.

These huge differences in cross-sectional, measured TFPs have spawned a literature investigating why productivity differences are so large. One explanation is simply measurement error: e is dominated by noise added to the dependent variable, output y. However, measured productivity e is persistent across time, meaning any measurement error cannot be transient (Baily, Hulten and Campbell, 1992). Managerial competence or overall business strategies are another major explanation (Bloom and Van Reenen, 2007). A well run business will produce more from the same inputs. Business strategy is likely to play even more of a role when one considers that the dependent variable in a productivity regression y is typically firm sales or value added, and the pricing decision of a firm affects sales (Foster, Haltiwanger and Syverson, 2005). Also, firms likely use technologies of varying qualities due to previous R&D decisions (Doraszelski and Jaumandreu, 2006).

Economists since at least Griliches (1957) have put forward another hypothesis: the quality of inputs l and k varies across firms. Economists working with US manufacturing plant data typically measure inputs as the dollar value of physical capital and the number of workers at a firm. At best, employees are separated into production and nonproduction workers. Not surprisingly, labor and capital vary in much greater detail. Two types of machines may have different uses and may not be perfect substitutes, and two types of workers may not have the same contributions to firm output. Our first contribution is to disaggregate the labor input. We use matched employer-employee data from Denmark to precisely measure many characteristics of workers at a firm. Schooling, sex, total experience and industry tenure proxy for general or occupation-specific human capital inputs. Tenure at a worker's current firm proxies for firm-specific human capital.

Following Griliches (1957), our production function includes a quality-weighting function that transforms firm-level measures of individual worker characteristics into efficiency units of labor. This labor quality function is embedded in the estimation of an otherwise standard Cobb-Douglas production function. The residual from this production function estimate is a firm's total factor productivity (TFP). We examine whether adjusting for labor input quality reduces the measured within-industry dispersion in residual TFP (RTFP), or the standard deviation of e. As RTFP is just a residual, we examine to what degree do labor input quality measures increase the fit to output data. Fit is measured by $R^2 = 1 - \frac{\text{Var}(e)}{\text{Var}(y)}$.

Standard models predict that more productive firms use more inputs. If true TFP is correlated with inputs, then our production function estimates will be biased and our residuals e will not consistently estimate a firm's true TFP. Griliches and Mairesse (1998) suggest that panel data approaches are very sensitive to measurement error. Consequently, we use cross-sectional variation to correct for the potential correlation of inputs with the unmeasured TFP term. We parametrize the intercept (mean TFP) with observable characteristics such as firm age and recent firm growth that are likely correlated with TFP. Also, we adopt (the simultaneity part of) a strategy inspired by Olley and Pakes (1996). Conditional on a firm's non-TFP state variables, its physical capital and firm age, under some modeling assumptions a firm's investment provides a proxy for its productivity. We add a polynomial in capital, investment and firm age in order to proxy for a firm's unobserved TFP.[1]

The Olley and Pakes (henceforth OP) procedure produces a direct, structural estimate of TFP. In other words, the OP procedure decomposes composite error terms $e = \omega + \eta$ into ω, structural TFP, and η, measurement error. Our second contribution is to examine to what degree this structural estimate of productivity ω explains measured dispersion in RTFP, or e.

OP is typically used to correct estimates of input elasticities β_k and β_l for the correlation of inputs with ω. The structural estimates of ω are not of primary interest if input elasticities are the objects of interest. However, much of the productivity literature focuses on the puzzle that the cross-sectional dispersion in measured RTFP is so large. To this end, the direct, structural estimates of TFP ω in OP have the potential to solve the RTFP puzzle.

We show that, consistent with the US manufacturing plant evidence, there is large degree of measured RTFP dispersion across Danish firms. With only the number of workers and the dollar value of capital as inputs, we find that a firm with one standard deviations more log RTFP has in RTFP levels $\exp(0.54) - 1 = 0.72$ times more output for the same inputs, in manufacturing. For three other sectors, our measured TFP dispersion is even higher.

Note that from now on, we automatically translate the standard deviation of log RTFP into RTFP levels by the function $\exp(\text{sd}(\log \text{RTFP})) - 1$.[2] This reports the difference in multiples in RTFP for firms one standard deviation of log RTFP away. We define $\sigma = \exp(\text{sd}(\log \text{x})) - 1$, where x is typically RTFP and the units of σ are in multiples. One standard deviation is conservative; $\exp(2 \cdot \text{sd}(\log \text{RTFP})) - 1$ is a much bigger number.

[1] See Van Biesebroeck (2007a) for a comparison of OP to other simultaneity-correction methods.

[2] The standard deviation of log RTFP is related to R^2 by the formula $\text{sd}(\log \text{RTFP}) = \sqrt{(1 - R^2)(\text{Var}(y))}$, where y is log value added.

We find that human capital inputs are correlated with firm value added. In other words, the coefficients on our labor quality measures have economically large magnitudes that are typically statistically distinguishable from zero.

However, the magnitude of the decrease in RTFP dispersion from including labor quality measures is small, for most sectors. For manufacturing, σ drops from 0.72 to 0.68 multiples.

Finally, we find that the Olley and Pakes (1996) structural TFP drops σ hardly at all in manufacturing: σ stays at 0.70 multiples. Adding the OP structural productivity term ω does not increase the statistical fit, R^2, of log-productivity regressions ($\Delta R^2 = 0.002$), even if input elasticities are precisely estimated in large samples.

Combining labor quality and the structural estimation of true productivity ω, we find that σ drops from 0.70 to 0.67 multiples.

The estimates show that the OP structural TFP ω has a σ for true TFP of 0.12 multiples. As above, the OP RTFP σ excluding ω is 0.70 multiples, much higher than 0.12. The OP structural interpretation of the original, non-OP measured, residual TFP dispersion is that it is dominated by measurement error. Another interpretation consistent with OP is that η represents contributions to productivity that occur after investment decisions are made.

The OP structural interpretation of η as measurement error conflicts with the literature's view that as RTFP is autocorrelated at the plant and firm levels, RTFP dispersion is not caused by classical, independent across time measurement error (Baily et al., 1992). Any measurement error is time persistent. We find that the year 2000 OP measurement error has a correlation of 0.80 with the same-firm year 2001 OP measurement error, in manufacturing. Thus, η is less likely to represent innovations in productivity after investment decisions are made.

Our results have several implications for production function estimation. First, inferences about across-firm RTFP dispersion are not sensitive to measurement error in input quality. For many research questions, using the number of workers rather than more detailed input measures will suffice. Second, including the OP structural measure ω does not reduce RTFP dispersion by a large magnitude. In terms of statistical fit, adding investment to a productivity regression explains little of the RTFP dispersion.

Third, the high autocorrelation in OP's structural measurement error η suggests the possibility that not all of this term is really measurement error. In terms of statistical fit, again this suggests that ω does not capture all differences in productivity across firms.

Fourth, in terms of consistent estimation of the input elasticities (omitted variable bias), the high autocorrelation in η is a violation of a maintained assumption of OP, unless η is not used to make input decisions by firms. The typical concern with endogeneity is that more productive firms use more inputs. OP's theoretical inversion procedure investment to be monotone in a scalar unobservable. A firm may have multiple unobservables such as demand shocks and input price shocks.[3] With multiple unobservables, OP is not a consistent estimator of input elasticities, ω and η. Even if the true η is measurement error, the accounting reports with measurement error could be forwarded to executives and used to make decisions. If firms use the true η to make input decisions, then OP will not be consistent for the input elasticities, ω and η.

Overall, our results show that the high cross-sectional dispersion in measured productivities is not explained by input qualities and the most commonly used structural productivity estimator. For measuring productivity, we find evidence against the reasonable conjecture by (Griliches, 1957) that a large part of productivity dispersion comes from mismeasured inputs. We return to this point in our conclusion.

The original paper by Olley and Pakes (1996) has inspired many methodological advances, such as Levinsohn and Petrin (2003) and Ackerberg, Caves and Frazer (2007).[4] As Ackerberg et al. argue, the consistency of OP and related methods rely on the ability to decompose e into ω and η. Still, none of these papers report statistics on the decomposition of e into the structural TFP ω and measurement error η components. OP work with e as a composite error term.[5] Using the composite residual e rather than the structural decomposition allows comparisons between RTFP in studies using OP and other studies. However, the structural interpretation is necessary to understand whether OP explains the large measured RTFP dispersions with structural measurement error or true productivity.

Several recent papers combine worker and output data, either to compare the production and wage regression coefficients (Van Biesebroeck, 2007b) or to control for worker ability in wage regressions (Frazer, 2006). We are focused on firm productivities and do not consider wages. The statistical fit labor input quality aspect of our work is similar to Hellerstein and Neumark (2006), who also find a low reduction in RTFP when adding labor quality measures using US manufacturing data. The magnitudes of the RTFP dispersion reduction are hard to compare between the two papers because Hellerstein and Neumark include materials as an input (which raises R^2), while our measure of output is value added. We also use labor history measures (experience, industry tenure and firm tenure) constructed from 21 years of panel data for all Danish citizens, and include four industry sectors, of which only one is manufacturing.

[3] For example, a firm may produce products with a limited market, meaning that advances in productivity do not encourage the firm to expand its output.

[4] See Doraszelski and Jaumandreu (2006) for another approach that uses a parametric first order condition for labor demand rather than a nonparametric control function.

[5] OP discuss this decision in their footnote 33 on page 1287. In their empirical application, OP focus on same-plant TFP growth, not the level of TFP across plants at the same point in time. OP do not report R^2 or other measures of fit.

2 Production functions

2.1 Overview

A production function takes inputs and produces outputs. Our measure of output is a firm's value added, which is just total sales minus materials and other outsourced inputs, such as consulting services. Subtracting materials from sales is valid if materials and other inputs combine using a Leontief production function. At least in manufacturing, a fixed-proportions materials technology is realistic as a given product often requires particular ingredients.[6]

The "total factor" in TFP refers to including two inputs, labor and capital. The residual e is, without structural interpretation, the output residual and hence the residual to log measured TFP. Total measured log TFP is $\beta_0 + e$, so the variance of e is the variance in residual TFP, or RTFP. The puzzle we seek to explain is why the estimated standard deviation of the residual e across plants, measured RTFP dispersion, is so high. As $R^2 = 1 - \frac{\mathrm{Var}(e)}{\mathrm{Var}(y)}$, we wonder why the statistical fit of log-valued added production functions is so poor.

2.2 Labor quality

We first investigate one explanation for the low R^2 and consequently high dispersion in measured RTFP: quality differences in labor inputs. As workers with more schooling and experience are paid higher wages, it would not be surprising to find that those workers contribute more to output. If one can only measure the total number of workers l, then the deviation between the true and measured efficiency units of labor will enter the error term and increase measured TFP dispersion, while at the same time causing an estimation bias due to measurement error.

Following a suggestion by Griliches (1957), we view the labor input as the number of workers times labor quality. Each worker is a bundle of measured characteristics. We unbundle workers so that labor quality is a function of the fraction of workers in a firm with each characteristic. In a firm with 100 workers, hiring 1 more woman with a college degree will increase the fraction of workers who are women by 1% and the fraction of workers with college degrees by 1%. Let x_{female} be the fraction of workers who are women, and x_{college} the fraction with a college degree. Total labor quality has the multiplicative functional form

$$q_\theta(x) = (1 + \theta_{\text{female}} x_{\text{female}}) \left(1 + \theta_{\text{college}} x_{\text{college}}\right). \qquad (2)$$

Here, efficiency units of labor are measured in some base units: the relative productivity compared to a male high-school graduate, say. In this case, θ_{female} is how much more productive a woman is relative to a man,

[6]While not reported, our conclusions about RTFP dispersion are robust to estimating a CES instead of Cobb-Douglas production function.

and θ_{college} is how much more productive a college educated worker is relative to a worker who did not attend college. A firm of all men where 100% of its workers attend college will have a per-worker quality of $1+\theta_{\text{college}}$. Note that a multiplicative labor quality measure is also used in Hellerstein and Neumark (2006).

Labor quality is not additively separable across workers, as in Welch (1969). For example, expanding the specification of $q_\theta(x)$ above produces the interaction term $\theta_{\text{female}}x_{\text{female}}\theta_{\text{college}}x_{\text{college}}$. If the θ's are positive, adding a male college graduate will produce a greater increase in labor quality at a firm with more women.

Let the total number of workers at a firm be n. The total labor input is then $l = n\cdot q_\theta(x)$. Substituting this expression for l in the Cobb-Douglas production function (1) gives the estimating equation

$$y = \beta_0 + \beta_l n \cdot q_\theta(x) + \beta_k k + e.$$

The parameters θ enter this equation nonlinearly, so estimation is by nonlinear least squares. It would be ideal to also measure the quality of physical capital, k. Our accounting data do not allow us to measure physical capital in other than monetary terms.

2.3 Olley and Pakes (1996)

Both true TFP ω and measurement error η cause unmeasured variation in y, so, following Olley and Pakes (1996), we set $e = \omega + \eta$. Marschak and Andrews (1944) introduced the concern that $\text{Cov}(l,\omega) > 0$ and $\text{Cov}(k,\omega) > 0$, or that more productive firms systematically use more inputs. This leads to a standard endogeneity problem, where the contributions from productivity are misattributed to inputs.

One solution is to parametrize mean log TFP, β_0, as a function of observable firm characteristics such as firm age and recent firm growth. If these variables partially proxy for ω, then the remaining $\tilde{\omega}$ will be less correlated with the measured inputs. Also, the measurement error η will play a larger role in the new $\tilde{e}$, as previous components of ω are captured by observables.

Our other approach to dealing with the cross-sectional correlation of inputs and TFP residuals is inspired by Olley and Pakes (1996) or OP.[7] Following OP, we estimate the Cobb-Douglas production with firm age included as a measurable component of TFP:

$$y = \beta_0 + \beta_a a + \beta_l l + \beta_k k + \omega + \eta.$$

OP use a theoretical model of a forward-looking firm where capital is slowly accumulated. Let i represent investment. OP's model shows that, between two firms with the same physical capital k and age a, the firm

[7] Ackerberg et al. points out inconsistencies in the arguments of Olley and Pakes and Levinsohn and Petrin. There is an alternative set of assumptions that justify OP.

with the higher TFP invests more:

$$i_1 > i_2 \text{ if } k_1 = k_2, a_1 = a_2 \text{ and } \omega_1 > \omega_2. \quad (3)$$

If there is no measurement error in inputs, one can use a nonparametric function $\phi(i,k,a)$ of investment and capital to proxy for the contributions of non-age TFP and the direct contributions of the inputs a and k. According to OP's model,

$$\phi(i,k,a) - \beta_k k - \beta_a a - \beta_0 = \omega,$$

and so an estimate of $\phi(i,k,a) - \beta_k k - \beta_a a - \beta_0$ is an estimate of ω. This point is important: $\phi(i,k,a)$ is not only a control function to correct for the simultaneity bias, $\phi(i,k,a) - \beta_k k - \beta_a a - \beta_0$ equals the structural TFP ω, according to OP's model.

We implement the simultaneity portion of OP in two steps:

1. Regress y on l and $\phi(i,k,a)$ to estimate β_l, and the labor quality variables when included. The R^2 from this step is the total explanatory power of inputs and structural productivity: $\beta_l l$, $\beta_k k$ and ω. This R^2 is one of our main focuses.
2. Regress $y - \hat{\beta}_l l$ on a, k and a polynomial in the term $\hat{\phi}(i,k,a) - \beta_a a_{t-1} - \beta_k k_{t-1}$, where $t-1$ refers to the year 2000 instead of 2001. Nonlinear least squared must be used as β_a and β_k enter the polynomial nonlinearly. This step is motivated by a panel data moment condition.

We estimate separately for four sectors, so we can control as best as possible for unmeasured input prices entering the inversion ϕ. To address whether our results arise from pooling too many heterogeneous industries, we also list separate results for a manufacturing industry with a large number of firms.

We produce estimates for the year 2001, although the second stage also uses firm-level data from 2000. We do not implement OP's selection-correction procedure for endogeneous entry and exit. Our primary goal is to structurally estimate ω and identify the magnitude of its cross-sectional variation across firms. We treat the estimated ω as an observable and add its contribution to R^2.

We conjecture that tweaks to the procedure will not cause dramatic increases in the R^2 of the first stage, which comes from adding a polynomial in a, k and i to a standard Cobb-Douglas production function. Ignoring nonlinearities, we measure whether adding investment and firm age to a production function noticeably increases R^2. To preview, we find that it does not.

2.4 Labor as a dynamic choice variable

OP relies on the idea that labor is a static choice variable. Given that we find a positive correlation between value added and inputs such as workers' tenure at a firm, the labor input is likely to be chosen with regard to last period's stock of labor. This is a problem with the OP structural interpretation of ω as true productivity, but not the facts about R^2, which are purely about data fit.

Ackerberg, Caves and Frazer (2007) modify OP to treat labor and physical capital symmetrically: labor can be a dynamic input. In a first stage, one regresses output y on $\phi(i,k,l,a)$, a polynomial in investment, capital, labor and firm age. The R^2 from this regression is the total explanatory power of inputs and structural productivity ω. In unreported results, we implement this procedure by adding labor to the polynomial. Not surprisingly, R^2 goes up very little.

3 Danish labor and accounting data

We need data on a firm's inputs and its output as well as measures of labor quality to estimate the impact of labor quality variables in the production function.

We use accounting data for capital, value added and investment. The accounting data come from Købmanstandens Oplysningsbureau (KØB), a Danish credit rating agency. The accounting data are an unbalanced panel that roughly covers the period 1995-2003 and use each firm's proprietary accounting period. We rescale the accounting variables to a twelve-month, calendar year basis. The accounting data were designed foremost to provide financial information for firms currently operating in 2003. We look at the year 2001 to maximize the number of firms with complete calendar year data. The OP second stage uses 2000 data, and we inflate 2000 monetary values to 2001 units.

We use value added as a measure of output and fixed assets for capital. Value added is reported for many more firms that total sales, perhaps because of the role of value added in value added taxes. We disregard firms who do not have rescaled accounting information on valued added and fixed assets for a 12 months period. For the labor input, we count the total number of workers in IDA, which is described below.

Firm age is directly reported in the accounting data. We include the log of firm age in some specifications.

We construct investment from the accounting data in order to estimate true TFP ω using the OP approach. Investment is computed using the formula $i = k_{2001} - (1-\delta)\,k_{2000}$, where δ is the depreciation rate. Investment cannot be missing and firms must be present in both 2000 and 2001. The accounting data report δk_{2000}, which we use to back out δ. We experimented with the Levinsohn and Petrin (2003) procedure to proxy for productivity using capital and materials inputs. We defined materials as total sales minus value added. However, we have data on total sales and hence materials for a small sample of firms. As this sample is highly selected, we do not report the Levinsohn and Petrin estimates.

To construct labor quality variables, we use the Danish Integrated Database for Labor Market Research (IDA), one of the central registers of Statistics Denmark. IDA integrates three types of data. The first dataset provides information at the individual level on demographics (age, sex, martial status, family status) and schooling for all Danish citizens over 1980–2001. Each individual is given a unique identification number that can be further used for matching with the other datasets of IDA. The second dataset of IDA is at the level of an individual's job. It contains information on individual labor earnings and labor market variables and the number of years of labor market experience. Labor market experience is computed since 1964.

Both full and part time jobs are included, but in the rare case of a worker with three or more jobs, only the primary and secondary jobs are reported. The data also contain a unique identification number for each job's establishment. IDA's establishment data provide a firm identification number that can be use for matching with other firm-level data.

We use IDA for 1980–2001 to compute labor market history variables such as firm tenure and industry tenure. Experience is calculated by Statistics Denmark. We compute firm tenure as the number of years a worker has been attached to a given firm. As we are concerned with spurious changes in firm identification codes over time, a worker's tenure is reset to zero only if both his firm and establishment identifiers change at the same time. We construct industry tenure using the following eight industry sectors: (1) agriculture and mining, (2) manufacturing, (3) construction and transport, (4) retail, hotels and restaurants, (5) finance, real estate and R&D activities, (6) public sector, (7) private households and extraterritorial activities and (8) others.

Industry is recorded at the establishment level. For our regressions, a multi-establishment firm's industry is the weighted (by number of workers) modal establishment industry.

All inputs are constructed at the firm level. We construct firm-level fractions of workers who have a given characteristic, say a college degree or 6–9 years of firm tenure. The intervals are simple to interpret as each measure is a fraction between 0 and 1. The intervals allow us to examine nonlinearities across the intervals, and they handle topcoding from not observing firm and industry tenure for spells starting before 1980. We then match the firm characteristics to the accounting data using the firm identification numbers provided by Statistics Denmark.

We estimated production functions for two samples: all firms with nonmissing variables and a sample with outliers removed. We are worried about possibly non-classical measurement in the accounting data, so we removed the firms in the top and bottom 1% of output to labor and physical capital to labor ratios. Removing these outliers increases the base R^2's substantially, but does not change the ΔR^2's from labor quality and OP much at all. We report specifications with the outliers removed, but our main conclusions about ΔR^2's are similar if we include the outliers.

4 Sample statistics by sectors

We only consider private-sector firms that have at least ten employees. We group lower-level industries into four sectors: (i) manufacturing, (ii) construction and transportation, (iii) retail, hotels and restaurants and (iv) finance, real estate and R&D activities. Unfortunately, Denmark is a small country and there are few firms in each more narrowly defined industry, although we sometimes include lower-level industry fixed effects. To see whether pooling industries affecting our results, we also separately estimate production functions for a manufacturing industry with a large number of Danish firms: machinery & equipment. We look at a cross section of firms in the year 2001.

Table 1 lists summary statistics for each large sector. The second line documents our dependent variable: the standard deviation in log value-added. The standard deviation of log value added in manufacturing is 1.21, meaning that a 1-standard deviation higher log value added corresponds to a σ of $\exp(1.21) - 1 = 2.35$ multiples in value added.

Finance is the most (measured) capital intensive sector and retail and construction are the least. Manufacturing has the most workers per firm at 79, and construction the least with 40. Recall we consider only firms with ten or more workers.

The other summary statistics report information on workforce composition. The fraction of female workers is the highest in finance and retail and the lowest in manufacturing. The finance sector has the most highly educated workforces. Workforces in manufacturing and construction have the highest experience levels. Finally, workforces in finance have lower firm and industry tenure than other industries' workers.

The standard deviations of the human capital inputs show that there is a reasonable amount of variation in the characteristics of workforces within each sector. Many standard deviations are similar in magnitude to the means themselves. Finance has the highest standard deviations, followed by retail, construction and finally manufacturing. The standard deviations are important, because any reduction in TFP dispersion (an increase in R^2) comes from both variation in workforce composition across firms as well as the estimated parameters on the labor quality measures.

5 Production function estimates w/o labor quality

Table 2A reports estimates of production functions such as (1) for the manufacturing sector. The first column uses all observations with nonmissing value added and capital, while the second column uses only observations with positive numbers of both college and noncollege workers. The college sample is then used to break out the number of workers into college and noncollege (third column) and then to add firm observables that could proxy for TFP, such as the log of firm age (fourth column) and three digit industry dummies. In an unreported specification, we add a five year growth measure due to Davis and Haltiwanger (1992). Compared to the baseline in the second column, R^2 increases from 0.798 to 0.803 from breaking labor inputs into college and noncollege, and from 0.803 to 0.815 from adding firm age and the full set of three-digit industry dummies.

Firm age, schooling and industry heterogeneity in mean TFP are not the keys to understanding cross-sectional dispersion in RTFP. With a R^2 of 0.815, $\frac{\text{Var(e)}}{\text{Var(y)}} = 0.185$, so measured RTFP comprises 19% of the variation in log output across firms.

As an aside, the sum of the coefficients on the numbers of college and noncollege workers in third column is only 0.019 different from the coefficient on the total number of workers in the second column. Also, while we do not impose constant returns to scale, an estimate very close to it always appears.

The fifth column of Table 2A reports estimates using the simultaneity-correction procedure of Olley and Pakes (1996), as discussed in Section 2.3. The estimation uses a reduced sample because of missing investment data. Investment data are needed for both 2000 and 2001 because of the OP second stage. For comparison, the sixth column contains an OLS specification on the sample of manufacturing firms with nonmissing investment. The estimates in the sixth column are not identical to but look similar to those in the third column with the larger college sample. Therefore, we suspect the missing investment data do not dramatically alter our results.

The OP procedure changes the point estimates only a little. Also, the R^2 increases by only 0.002 when we structurally estimate ω, the true TFP in OP, and include ω as a regressor (coefficient is 1) that contributes to R^2. Later we will directly calculate the standard deviation of log RTFP. For now, it appears that OP will not reduce measured RTFP a lot. The estimated standard deviation of ω is 0.12. This is not small, but a σ of 0.12 (12%) is smaller than the σ of 0.70 for OLS applied to the OP estimation sample and the σ of 0.70 for the measurement error in the OP estimates. The later numbers appear in Table 7; we will discuss them soon.

One question is whether the structural measurement error η is i.i.d. over time. Table 2A shows it is not: the same-firm correlation between η in 2000 and 2001 is 0.80.

Tables 3A, 4A and 5A repeat the above analysis for construction, retail and finance, respectively. The base coefficient estimates and the base R^2's vary across sectors. R^2's are lower in the three sectors other than manufacturing. This likely reflects the greater heterogeneity in technology in these sectors. Below we use a narrower industry grouping to better control for heterogeneous technologies.

Disaggregating college graduates from other workers increases R^2 (compare columns (2) and (3) in Tables 3A, 4A and 5A) by -0.008 in construction, a large 0.056 in retail and 0.004 in finance.

Adding firm age and industry indicators increases R^2 by 0.017 in construction, 0.051 in retail, and 0.051 in finance. While not large compared to the 35% of log value added variance explained by residuals, these can be considered large ΔR^2's reflecting measured differences in log TFPs.

Comparing columns (6) and (5) in Tables 3A, 4A and 5A gives changes in R^2 due to the OP procedure of 0.006 in construction, 0.011 in retail, and 0.018 in finance. These are relatively small ΔR^2's compared to the typically 35% of log value added variance explained by measurement error in the structural OP interpretation. Again, these results will be explained in more detail soon.

As for the input elasticities, the OP procedure noticeably decreases the coefficient on physical capital in construction (Table 3A) and finance (Table 5A). An upward bias is predicted by the univariate OLS endogeneity bias formula when more productive firms use more capital, so the effects of unmeasured productivity (the error term) are falsely attributed to the inputs in OLS. However, the typical suspicion in the literature is that capital coefficients are underestimated. Note that the OP estimate of the capital coefficient comes from a panel data moment condition, not just including investment as a regressor.

Our industrial sectors cover much more than the typical manufacturing industries studies in the productivity literature. However, our sectors do pool potentially heterogeneous industries because of the limited size of Denmark. To address pooling, Table 6A considers a narrower manufacturing industry with a large number of firms: machinery and equipment. Compared to all manufacturing firms in Table 2A, the results for machinery show that OP increases R^2 by 0.012, while adding TFP controls increases R^2 by only 0.004. In a more disaggregated sector, the relative ΔR^2's of OP and TFP controls are reversed, but the bottom line remains that both ΔR^2's are small.

6 Production function estimates with labor quality

6.1 Statistical fit

Tables 2B, 3B, 4B and 5B report estimates of production functions with labor quality measures. The functional form for labor quality is equation (2).

Look at column 1 in Table 2B, for manufacturing. This uses the same sample as column 2 in Table 2A. We see that adding the labor quality measures increases R^2 from 0.798 or 0.815, so $\Delta R^2 = 0.017$. In column 2 of 2B, adding firm age, five year growth according to a Davis and Haltiwanger (1992) measure, and 3-digit industry indicators increases R^2 by 0.012. This is identical to the ΔR^2 of 0.012 from adding TFP controls recorded in columns 3 and 4 of Table 2A.

Column 3 of Table 2B adds a standard OP correction to the labor quality specification. Compared to column 5 of Table 2A, adding labor quality increases the R^2 from 0.799 to 0.810, or $\Delta R^2 = 0.011$. Again, not a huge increase. For comparison, column 4 of 2B is a labor quality specification on the OP sample, but without using OP. Comparing columns 4 and 5 of 2B, we see that the incremental contribution of OP is again small: $\Delta R^2 = 0.002$.

Table 3B adds labor quality to the construction and transportation sector. Again, the changes in R^2's from adding TFP controls and the OP procedure are very similar to those in Table 3A, for the same sector. Adding labor quality to the OLS specification increases the R^2 by 0.022 (column 2 of 3A and 1 of 3B) and adding labor quality to the OP specification increases the R^2 by 0.027.

For retail, comparing the baseline column 2 of 4A to 1 of 4B involves a dramatic R^2 increase of 0.12, from 0.662 to 0.777. For OP, going from column 5 of 4A to 3 of 4B gives a still large change in R^2 of 0.054. For finance in Tables 5A and 5B, adding labor quality raises R^2 by 0.056, while for the OP model for finance the ΔR^2 is also 0.058. We suspect these dramatic increases result from the heterogeneity in these coarse industry groups.

Table 6B returns to our narrower sector: machinery and equipment. We see that moving from column 2 of 6A to 1 of 6B has a small ΔR^2 of 0.012. For OP, moving from column 5 of 6A to 2 of 6B also gives a small ΔR^2 of 0.012. In the machinery manufacturing industry, mismeasured labor inputs are not the key to the productivity dispersion puzzle.

6.2 Point estimates

Recall from equation (2) that the labor quality coefficients multiply the fraction of workers in each category. Consider manufacturing. In Table 2B's base specification in column (1), the coefficient on female is 0.168. This means that a firm that has 10% more women with have $0.1 \cdot 0.168 = 0.017$ or around 2% more labor inputs. Note that adding TFP controls, notable three-digit fixed effects, makes the female coefficient negative and small. The coefficients on schooling are high: in manufacturing a firm with a 10% higher fraction of college graduates has 18% more labor inputs.

The baseline coefficients on firm tenure are around 0.3 for most categories. The excluded category is newcomers: those workers with zero years of firm tenure. A firm where 10% of the workers switch from being newcomers to workers with one year of tenure will have 3% higher labor inputs. However, these workers will not continue to produce more labor inputs because of firm tenure alone: the point estimates actually decrease, likely the effect is merely to not be a newcomer. Adding TFP controls including firm age (Table 2B column (2)) makes the firm tenure coefficients have a more standard upward-sloping profile until the last category, although the standard errors are still large. This is not surprising because firm age is correlated with the workforce's firm tenure.

In all columns of Table 2B, the point estimates for the coefficients on industry tenure are not necessarily economically small, but the coefficients are small relative to the standard errors.

Total labor market experience enters as a mean number of years, and has a positive and economically large magnitude in all specification in Table 2B.

Table 3B, for construction, has smaller female and schooling point estimates than those in Table 2B for manufacturing. Some of the general human capital coefficients in Table 4B, for retail, restaurants and hotels, are economically quite large. In retail, a firm with 10% more college graduates is predicted to have 30% more labor inputs. The experience measure is also large: a firm with 5 more years of mean experience in its workforce will have 57% more labor inputs.

In Table 5B, for finance, the most divergent coefficients are those on industry tenure. In finance, the industry tenure variables have large and statistically distinct from zero coefficients, a contrast with the other three sectors. Also in finance, the last two firm tenure categories have negative coefficients. A firm moving from 10% to 0% workers with 3–5 years of firm tenure and 0% to 10% workers with 6–9 years of tenure will have $1-(1-0.1\cdot 0.456)\,/\,(1+0.1\cdot 0.002)=4.6\%$ lower labor inputs.

6.3 Interpretation under endogeneity

While studies such as Hellerstein and Neumark (2006) and Van Biesebroeck (2007b) emphasize interpreting the point estimates, we are cautious because such interpretations require a convincing argument that the labor inputs are uncorrelated with the error term. While under its maintained assumptions the OP procedure structurally estimates ω, the true TFP term, that may or may not be true under alternative assumptions.

However, we conjecture that our estimates of the orders of magnitude in changes in R^2's from adding labor quality controls are less sensitive to endogeneity problems. A large part of the changes in R^2 involve the cross-sectional variation in labor inputs across firms, and in calculating R^2 that variation would remain fixed even if the estimated coefficients change from endogeneity correction.

7 Changes in TFP dispersion

Recall that $R^2=1-\frac{\mathrm{Var}(e)}{\mathrm{Var}(y)}$, where e is log residual total factor productivity (RTFP) and y is log value added. For OLS and NLLS (non-OP) estimators, we treat all components of the error term the same, so $\eta=e$. For OP, we treat ω as an observable and focus on the structural measurement error, η. We calculate the standard deviation of log RTFP as

$$\mathrm{SD}(\eta)=\sqrt{\left(1-R^2\right)\left(\mathrm{Var}(y)\right)}.$$

Our nonlogged measure σ is still $\sigma=\exp(\mathrm{sd}(\log \mathrm{RTFP}))-1$. Table 7 walks one through the calculation of σ for seven specifications for each of the four industrial sectors.

Figure 1 displays the changes in σ graphically. Consider manufacturing. In a base specification the σ is 0.71. So in the standard specification for manufacturing, a firm with one standard deviation more productivity is 3/4's more productive. Comparing firms two standard deviations apart gives a σ analog of 1.95 multiples.

Some firms have missing investment data, which are needed for the Olley and Pakes procedure. The sample with nonmissing data has a σ of 0.70 multiples.

Figure 1 shows how σ decreases when adding explanatory variables. In the specification with the most robust controls, combining the structural Olley and Pakes estimate of true productivity ω and detailed labor quality controls, σ drops from 0.70 to 0.67 multiples. A drop of 0.03 multiples from adding detailed labor market history variables, detailed schooling variables, and using a sophisticated structural procedure to estimate true productivity, ω, is not large.

Table 6 and Figure 1 show the largest change in σ from columns 5 to 7 is 0.14, in retail. Comparing the changes from columns 5 to 6 to the changes from columns 5 to 7 for retail, the latter are higher, corresponding to 4/5 of the total change of 0.13 between columns 5 and 8. The main change comes from adding labor quality rather than OP's ω.

Likewise, in the full, non-OP sample, adding the TFP controls firm age and three-digit industry indicators tends to reduce σ the most.

8 Implications for OP

Recall that our focus has been on the first stage of OP: the regression of log value added on log labor and the polynomial $\phi(i,k,a)$. We find that the ΔR^2 from adding a polynomial in investment, capital and firm age is low compared to a baseline OLS regression of using labor and capital, on the same sample. This is a statement about statistical fit: adding the polynomial does not increase R^2 much. The main reason is simply that investment is correlated with capital and labor, so adding investment does not explain much of the residual variation from OLS.

We used the OP second stage to find the OP structural TFP term, ω. A structural interpretation of the OP first stage is that adding the structural productivity term does not explain the measured dispersion in firm productivities. Tables 2A, 3A, 4A and 5A report the standard deviation of ω in column 5: it is economically non-trivial but much smaller than the standard deviation of the structural measurement error component, η, discussed above.

Our estimate of η is the residual from the OP first stage. By the linear least squares first order conditions, the residuals are numerically uncorrelated with the included regressors, labor and the terms in the polynomial $\phi(i,k,a)$. So by construction our estimate of OP's structural measurement error term is uncorrelated with inputs.

The one year autocorrelation in the same-firm OP estimates of η ranges from 0.78 to 0.85, ensuring that any measurement error cannot be explained by purely transient mistakes. The high autocorrelation also makes it likely that η does not represent innovations in productivity after investment decisions are made. A non-measurement error possibility where OP is still consistent is that many aspects of productivity are time persistent but not correlated with inputs. For example, a firm may produce a niche product with a limited potential market. Another possibility is that firms are limited in capacity, so more productive firms do not need more inputs. However, these arguments go against the spirit of OP's theoretical model, because they require investment to be monotone in one productivity term, and not to be a function at all of a second productivity term.

Again, by the least squares first order conditions, our estimate of η is uncorrelated with measured inputs. However, the first stage residual is only a consistent estimate of the theoretical η if the first stage of the OP procedure is consistent. Consistency requires the property in equation (3): conditional on observable states, investment is monotone in unobservable productivity. This condition can fail if firms face a different product situation or different input market prices, so that other unobservable state variables enter the firm's investment decision. Given what we know about the role of market power in industries, firms likely face different product market situations in ways not captured by a scalar TFP term such as ω.

If OP is inconsistent due to multiple unobservables, one likely outcome is that the η's estimated off the cross section will be correlated, as the residuals are picking up these other, presumably autocorrelated state variables for which ω is not a good proxy. Of course we have no data on unobservable state variables. However, our Occam's razor explanation for the autocorrelation in η is that it reflects multiple unobserved state variables, most likely demand conditions.

Even if OP is consistent, it is still the case that the structural estimate of ω is not the explanation for large, measured productivity dispersions. Either firm productivity is not as closely linked to input choices as some simple profit maximization models would suggest, or η really reflects large, time persistent measurement error in accounts that are not forwarded to executives to make input decisions. The true η, if ω could be consistently estimated, is probably a sum of factors including measurement error and productivity variation not correlated with inputs and investment.

9 Conclusions

A puzzle in empirical productivity studies is why some firms produce dramatically more measured outputs for the same measured inputs. This paper rules out two explanations.

Following a conjecture by Griliches (1957), we match our firm accounting data with 21-year panel data on all Danish citizens to compute detailed human capital inputs. We use these inputs to create a labor quality measure, and estimate the parameters of this input quality-augmented production function. Even though the labor quality coefficients are often statistically distinct from 0, we find changes in one standard deviation σ's (TFP level multiples) of 0.71 to 0.68, 0.78 to 0.73, 0.77 to 0.66, and 1.05 to 0.93, for our four industry sectors.

We also adopt an innovative structural estimator introduced by Olley and Pakes (1996). While the motivating for this procedure was originally to correct input elasticities for simultaneity bias, a side benefit is that OP provides a structural estimate of true TFP ω, as opposed to measurement error η. We estimate ω, treat it as an observable and assess the complete prediction equation's fit. We find changes in one standard deviation σ's of 0.70 to 0.70, 0.74 to 0.73, 0.77 to 0.75 and 1.07 to 1.02.

We also calculated the σ analog of the OP structural TFP ω. The true TFP σ ranges from 0.11 to 0.19, large values but not enough to explain the puzzle of RTFP σ's of 0.70 to 1.07 before OP was used.

We interpret reductions in RTFP dispersion from adding detailed labor quality measures and using a structural estimator for true productivity as small. Explanations with some empirical support include differences in research and development (Doraszelski and Jaumandreu, 2006), pricing (Foster et al., 2005) and business practices (Bloom and Van Reenen, 2007). Explaining these large dispersions remains an open question.

Our estimates have a few implications for methodology. First, if one is interested in estimating σ, disaggregating labor inputs will not dramatically decrease the estimate. For many questions, the number of workers is a good proxy for the labor input. Second, OP's productivity ω should not be used as a measure of true productivity, as the autocorrelation in η violates the spirit of OP's structural treatment of η as measurement error. To the extent that the OP theoretical inversion eliminates simultaneity bias, OP should improve the estimates of input elasticities. However, the high autocorrelation of η suggests that multiple unobservables may enter a firm's profit function, making OP potentially inconsistent.

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Table 1 - Summary Statistics by Sector

Variables	Manufacturing		Construction & Transportation		Retail, Hotels and Restaurants		Finance, Real Estate and R&D Activities	
	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.
Value added	30,800	123,400	14,700	187,700	20,300	95,600	50,300	535,400
Log value added	9.29	1.21	8.71	0.93	9.03	1.07	9.28	1.26
Capital	36,200	209,500	14,100	273,600	15,100	116,500	86,300	1,246,900
Labor	78.5	289.3	40.2	228.0	45.8	385.7	63.4	381.9
Investment*	8,100	39,200	3,600	29,600	5,500	40,900	12,500	99,500
Firm age	25.6	25.4	19.6	19.7	20.2	21.9	15.5	22.2
Experience	16.0	4.1	15.4	3.9	13.5	5.6	13.0	5.1
Female	0.28	0.21	0.13	0.14	0.37	0.25	0.43	0.21
College & master	0.07	0.09	0.03	0.07	0.06	0.10	0.28	0.24
Community college	0.05	0.06	0.04	0.06	0.04	0.07	0.07	0.09
Vocational	0.53	0.16	0.59	0.17	0.60	0.17	0.48	0.21
Firm tenure 1 to 2 years	0.24	0.14	0.26	0.14	0.27	0.15	0.31	0.18
Firm tenure 3 to 5 years	0.19	0.11	0.18	0.12	0.17	0.12	0.17	0.13
Firm tenure 6 to 9 years	0.14	0.11	0.12	0.11	0.11	0.10	0.09	0.11
Firm tenure 10 years and up	0.21	0.17	0.16	0.15	0.17	0.16	0.12	0.17
Industry tenure 1 to 2 years	0.21	0.15	0.22	0.13	0.23	0.14	0.27	0.18
Industry tenure 3 to 5 years	0.18	0.12	0.20	0.12	0.19	0.12	0.18	0.13
Industry tenure 6 to 9 years	0.16	0.12	0.16	0.11	0.14	0.11	0.12	0.11
Industry tenure 1o years and up	0.26	0.19	0.26	0.16	0.25	0.19	0.19	0.21
# observations	4,076		3,278		4,964		1,843	

* Note that there are missing data for investment. As to apply OP, we need firms with no missing data for investment, both in 2001 and 2000, the summary statistics for investment are for a smaller sample. The size of this restricted sample is 2404 observations for manufacturing, 1300 for construction, 1948 for retail and 969 for finance.

Table 2A - Production Function Estimates - Manufacturing

Dep. variable: Log Value Added	(1) Full sample		(2) Baseline		(3) College/non college		(4) TFP controls		(5) OP		(6) Spec. (3) on OP sample	
	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.
Log labor	0.848***	0.013	0.847***	0.015								
Log college					0.281***	0.011	0.258***	0.013	0.267***	0.013	0.279***	0.013
Log non college					0.547***	0.016	0.581***	0.017	0.524***	0.020	0.536***	0.020
Log capital	0.153***	0.008	0.144***	0.010	0.153***	0.010	0.138***	0.010	0.104***	0.015	0.156***	0.011
Firm age (log)							-0.0002	0.010	-0.019	0.012	-0.003	0.012
Constant	4.946***	0.048	5.049***	0.054	5.761***	0.060	5.857***	0.456	6.327***	0.634	5.791***	0.077
Industry dummies	no		no		no		3-digit		no		no	
R-squared	0.797		0.798		0.803		0.815		0.799		0.797	
OP structural TFP ω									1			
1-year autocorrelation of OP residuals - "measurement error"									0.796			
Std.dev. of OP structural TFP ω									0.123			
# observations	4,076		3,329		3,329		3,329		2,404		2,404	

(1) Cobb Douglas - full sample

(2) Cobb Douglas - sample with no missing log college and log non college

(3) Similar to (2) but with labor split into college vs. non college

(4) Similar to (3), adds the log of firm age and 3 digit industry dummies as TFP controls. In a specification not shown, we add firm growth over the last 5 years as an extra control. The coefficients estimates and R-squared were very similar

(5) OP 3rd stage: estimation of log value added on log college, log non college, log capital, log firm age and OP structural TFP ω . See the text for more information.

OP 1st stage: the college and non college coefficients were retrieved by re-estimating (3) with a second-order polynomial in capital, investment and firm age

OP 2nd stage: nonlinear estimation of (log value added - 0.268*log college - 0.468*log non college) on capital, firm age and a polynomial in the estimate of unobserved productivity retreives the estimates of the coefficients on capital and firm age

(6) Similar to (3) but with the same sample as (5)

***/**/* reports significance at 1/5/10%

Table 2B - Labor Quality Augmented Production Function Estimates

Manufacturing

Dep. variable: Log Value Added	(1) Baseline		(2) TFP controls		(3) OP		(4) Spec. (1) on OP sample	
	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.
Log labor	0.846***	0.015	0.863***	0.015	0.809***	0.019	0.831***	0.017
Log capital	0.142***	0.009	0.124***	0.010	0.010***	0.014	0.147***	0.011
Female	0.168***	0.065	-0.026	0.074	0.191**	0.083	0.199**	0.081
College & master	1.837***	0.208	1.628***	0.219	1.987***	0.277	2.019***	0.272
Community college	1.384***	0.000	1.138***	0.247	1.417***	0.305	1.505***	0.301
Vocational	1.057***	0.236	0.737***	0.170	0.763***	0.198	0.798***	0.198
Experience	0.046***	0.011	0.042***	0.010	0.045***	0.014	0.043***	0.013
Firm tenure 1 to 2 years	0.303**	0.154	0.371**	0.155	0.416	0.255	0.298	0.235
Firm tenure 3 to 5 years	0.273*	0.153	0.434***	0.162	0.123	0.216	0.041	0.202
Firm tenure 6 to 9 years	0.23	0.150	0.608***	0.189	0.197	0.217	0.107	0.204
Firm tenure 10 years and up	0.15	0.128	0.408***	0.159	0.109	0.194	0.024	0.179
Industry tenure 1 to 2 years	-0.06	0.111	-0.039	0.109	-0.004	0.185	0.050	0.187
Industry tenure 3 to 5 years	0.01	0.125	0.055	0.250	0.125	0.205	0.152	0.202
Industry tenure 6 to 9 years	0.05	0.128	0.066	0.128	0.219	0.207	0.228	0.202
Industry tenure 1o years and up	-0.211**	0.093	-0.265***	0.090	-0.086	0.158	-0.085	0.155
Firm age (log)			0.003	0.010	-0.017	0.012		
DH growth 5 years			0.068***	0.023				
Constant	4.032***	0.108	4.276***	0.148	4.812***	0.632	4.004***	0.138
Industry dummies	no		3-digit		no		no	
R-squared	0.815		0.827		0.810		0.808	
OP structural TFP ω					1			
1-year autocorrelation of OP residuals - "measurement error"					0.779			
Std.dev. of OP structural TFP ω					0.112			
# observations	3,329		3,329		2,404		2,404	

(1) Nonlinear estimation of a labor quality augmented Cobb Douglas production function

(2) Adds log of firm age, firm growth over the last 5 years and 3 digit industry dummies as TFP controls

(3) OP 3rd stage: estimation of log value added on log labor quality, log capital, log firm age and OP structural TFP ω. See in the text for more information. OP 1st stage: the labor and labor quality coefficients were retrieved by re-estimating (1) with a second-order polynomial in capital, investment and firm age. OP 2nd stage: nonlinear estimation of log value added minus labor quality on capital, firm age and a polynomial in the estimate of unobserved productivity retreives the estimates of the coefficients on capital and firm age

(4) Similar to (1) but with the same sample as (3)

***/**/* reports significance at 1/5/10%

Table 3A - Production Function Estimates - Construction and Transportation

Dep. variable: Log Value Added	(1) Full sample		(2) Baseline		(3) College/non college		(4) TFP controls		(5) OP		(6) Spec. (3) on OP sample	
	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.
Log labor	0.854***	0.016	0.851***	0.020								
Log college					0.193***	0.017	0.177***	0.019	0.169***	0.021	0.169***	0.021
Log non college					0.654***	0.022	0.671***	0.023	0.639***	0.028	0.653***	0.028
Log capital	0.110***	0.009	0.107***	0.011	0.122***	0.011	0.090***	0.013	0.047**	0.022	0.127***	0.014
Firm age (log)							-0.000	0.013	-0.009	0.019	-0.031*	0.017
Constant	5.216***	0.057	5.255***	0.069	5.712***	0.074	6.295***	0.144	5.986***	0.717	5.791***	0.104
Industry dummies	no		no		no		3-digit		no		no	
R-squared	0.628		0.668		0.660		0.677		0.669		0.663	
OP structural TFP ω									1			
1-year autocorrelation of OP residuals - "measurement error"									0.765			
Std.dev. of OP structural TFP ω									0.143			
# observations	3,278		2,099		2,099		2,099		1,300		1,300	

(1) Cobb Douglas - full sample

(2) Cobb Douglas - sample with no missing log college and log non college

(3) Similar to (2) but with labor split into college vs. non college

(4) Similar to (3), adds the log of firm age and 3 digit industry dummies as TFP controls. In a specification not shown, we add firm growth over the last 5 years as an extra control. The coefficients estimates and R-squared were very similar

(5) OP 3rd stage: estimation of log value added on log college, log non college, log capital, log firm age and OP structural TFP ω . See the text for more information.

OP 1st stage: the college and non college coefficients were retrieved by re-estimating (3) with a second-order polynomial in capital, investment and firm age

OP 2nd stage: nonlinear estimation of (log value added - 0.268*log college - 0.468*log non college) on capital, firm age and a polynomial in the estimate of unobserved productivity retreives the estimates of the coefficients on capital and firm age

(6) Similar to (3) but with the same sample as (5)

***/**/* reports significance at 1/5/10%

Table 3B - Labor Quality Augmented Production Function Estimates

Construction & Transportation

Dep. variable: Log Value Added	(1) Baseline		(2) TFP controls		(3) OP		(4) Spec. (1) on OP sample	
	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.
Log labor	0.856***	0.020	0.854***	0.020	0.822***	0.024	0.833***	0.026
Log capital	0.092***	0.012	0.075***	0.012	0.048**	0.019	0.101***	0.015
Female	0.911***	0.166	0.330**	0.166	0.902***	0.224	0.932***	0.224
College & master	1.430***	0.299	1.401***	0.323	1.294***	0.391	1.270***	0.385
Community college	0.310	0.250	0.300	0.296	0.248	0.321	0.222	0.316
Vocational	0.248*	0.131	0.337**	0.158	0.315*	0.183	0.304*	0.790
Experience	0.034***	0.011	0.042***	0.013	0.038**	0.016	0.039**	0.016
Firm tenure 1 to 2 years	0.356*	0.186	0.309*	0.181	0.499	0.356	0.541	0.355
Firm tenure 3 to 5 years	0.499**	0.199	0.584***	0.210	0.348	0.294	0.334	0.288
Firm tenure 6 to 9 years	0.291	0.189	0.567**	0.236	0.433	0.293	0.398	0.286
Firm tenure 10 years and up	0.114	0.157	0.522**	0.214	0.198	0.257	0.054	0.236
Industry tenure 1 to 2 years	-0.029	0.187	0.025	0.192	0.131	0.365	0.039	0.341
Industry tenure 3 to 5 years	0.144	0.201	0.190	0.205	0.522	0.398	0.412	0.378
Industry tenure 6 to 9 years	0.069	0.198	0.106	0.202	0.249	0.337	0.172	0.327
Industry tenure 1o years and up	-0.002	0.173	-0.129	0.161	0.008	0.295	0.047	0.290
Firm age (log)			-0.009	0.014	0.009	0.018		
DH growth 5 years			0.060**	0.028				
Constant	4.494***	0.146	4.628***	0.188	4.702***	0.712	4.382***	0.207
Industry dummies	no		3-digit		no		no	
R-squared	0.690		0.700		0.696		0.692	
OP structural TFP ω					1			
1-year autocorrelation of OP residuals - "measurement error"					0.769			
Std.dev. of OP structural TFP ω					0.110			
# observations	2,099		2,099		1,300		1,300	

(1) Nonlinear estimation of a labor quality augmented Cobb Douglas production function

(2) Adds log of firm age, firm growth over the last 5 years and 3 digit industry dummies as TFP controls

(3) OP 3rd stage: estimation of log value added on log labor quality, log capital, log firm age and OP structural TFP ω. See in the text for more information. OP 1st stage: the labor and labor quality coefficients were retrieved by re-estimating (1) with a second-order polynomial in capital, investment and firm age. OP 2nd stage: nonlinear estimation of log value added minus labor quality on capital, firm age and a polynomial in the estimate of unobserved productivity retreives the estimates of the coefficients on capital and firm age

(4) Similar to (1) but with the same sample as (3)

***/**/* reports significance at 1/5/10%

Table 4A - Production Function Estimates - Retail, Restaurants and Hotels

Dep. variable: Log Value Added	(1) Full sample		(2) Baseline		(3) College/non college		(4) TFP controls		(5) OP		(6) Spec. (3) on OP sample	
	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.
Log labor	0.892***	0.014	0.825***	0.017								
Log college					0.432***	0.011	0.359***	0.011	0.392***	0.014	0.412**	0.014
Log non college					0.488***	0.015	0.594***	0.015	0.478***	0.018	0.488***	0.019
Log capital	0.144***	0.008	0.147***	0.010	0.139***	0.009	0.102***	0.008	0.080***	0.013	0.141***	0.011
Firm age (log)							0.002	0.009	-0.035**	0.016	0.049**	0.013
Constant	5.060***	0.048	5.375***	0.060	6.191***	0.056	6.083***	0.134	5.658***	0.624	6.090***	0.080
Industry dummies	no		no		no		3-digit		no		no	
R-squared	0.661		0.662		0.718		0.769		0.743		0.732	
OP structural TFP ω									1			
1-year autocorrelation of OP residuals - "measurement error"									0.809			
Std.dev. of OP structural TFP ω									0.185			
# observations	4,964		3,270		3,270		3,270		1,948		1,948	

(1) Cobb Douglas - full sample

(2) Cobb Douglas - sample with no missing log college and log non college

(3) Similar to (2) but with labor split into college vs. non college

(4) Similar to (3), adds the log of firm age and 3 digit industry dummies as TFP controls. In a specification not shown, we add firm growth over the last 5 years as an extra control. The coefficients estimates and R-squared were very similar

(5) OP 3rd stage: estimation of log value added on log college, log non college, log capital, log firm age and OP structural TFP ω . See the text for more information.

OP 1st stage: the college and non college coefficients were retrieved by re-estimating (3) with a second-order polynomial in capital, investment and firm age

OP 2nd stage: nonlinear estimation of (log value added - 0.268*log college - 0.468*log non college) on capital, firm age and a polynomial in the estimate of unobserved productivity retreives the estimates of the coefficients on capital and firm age

(6) Similar to (3) but with the same sample as (5)

***/**/* reports significance at 1/5/10%

Table 4B - Labor Quality Augmented Production Function Estimates

Retail, Restaurants and Hotels

Dep. variable: Log Value Added	(1) Baseline		(2) TFP controls		(3) OP		(4) Spec. (1) on OP sample	
	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.
Log labor	0.948***	0.014	0.952***	0.014	0.911***	0.017	0.942***	0.017
Log capital	0.095***	0.008	0.085***	0.008	0.055***	0.011	0.099***	0.010
Female	0.131**	0.051	0.069	0.056	0.220***	0.074	0.162**	0.065
College & master	3.015***	0.215	2.602***	0.205	2.648***	0.268	2.733***	0.258
Community college	2.539***	0.238	2.175***	0.231	2.724***	0.320	2.922***	0.310
Vocational	0.960***	0.166	1.081***	0.182	0.867***	0.217	0.805***	0.194
Experience	0.114***	0.014	0.041***	0.007	0.138***	0.024	0.145***	0.023
Firm tenure 1 to 2 years	0.273**	0.124	0.226*	0.116	0.372*	0.225	0.324	0.200
Firm tenure 3 to 5 years	0.224*	0.127	0.181	0.122	0.242	0.212	0.198	0.192
Firm tenure 6 to 9 years	0.210	0.137	0.082	0.137	0.296	0.226	0.347	0.212
Firm tenure 10 years and up	-0.238**	0.096	-0.232**	0.102	-0.147	0.172	-0.232	0.149
Industry tenure 1 to 2 years	-0.040	0.113	0.037	0.114	-0.257	0.180	-0.268	0.166
Industry tenure 3 to 5 years	0.070	0.124	0.163	0.124	-0.129	0.208	-0.154	0.190
Industry tenure 6 to 9 years	0.158	0.132	0.268**	0.131	-0.057	0.219	-0.140	0.196
Industry tenure 1o years and up	0.048	0.109	0.293**	0.119	-0.046	0.203	-0.103	0.184
Firm age (log)			-0.027***	0.10	-0.077***	0.014		
DH growth 5 years			-0.040**	0.018				
Constant	3.594***	0.100	3.973***	0.113	4.104***	0.567	3.659	0.132
Industry dummies	no		3-digit		no		no	
R-squared	0.777		0.795		0.797		0.788	
OP structural TFP ω					1			
1-year autocorrelation of OP residuals - "measurement error"					0.832			
Std.dev. of OP structural TFP ω					0.146			
# observations	3,270		3,270		1,948		1,948	

(1) Nonlinear estimation of a labor quality augmented Cobb Douglas production function

(2) Adds log of firm age, firm growth over the last 5 years and 3 digit industry dummies as TFP controls

(3) OP 3rd stage: estimation of log value added on log labor quality, log capital, log firm age and OP structural TFP ω. See in the text for more information. OP 1st stage: the labor and labor quality coefficients were retrieved by re-estimating (1) with a second-order polynomial in capital, investment and firm age. OP 2nd stage: nonlinear estimation of log value added minus labor quality on capital, firm age and a polynomial in the estimate of unobserved productivity retreives the estimates of the coefficients on capital and firm age

(4) Similar to (1) but with the same sample as (3)

***/**/* reports significance at 1/5/10%

Table 5A - Production Function Estimates - Finance, Real Estate, R&D and Business Activities

Dep. variable: Log Value Added	(1) Full sample		(2) Baseline		(3) College/non college		(4) TFP controls		(5) OP		(6) Spec. (3) on OP sample	
	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.
Log labor	0.852***	0.023	0.851***	0.023								
Log college					0.381***	0.016	0.402***	0.019	0.361***	0.023	0.379***	0.021
Log non college					0.464***	0.019	0.398***	0.022	0.415***	0.021	0.436***	0.025
Log capital	0.163***	0.012	0.159***	0.012	0.166***	0.012	0.142***	0.013	0.140***	0.017	0.182***	0.017
Firm age (log)							0.023	0.016	0.168	0.023	-0.001	0.023
Constant	5.171***	0.079	5.234***	0.081	5.964***	0.080	6.083***	0.108	8.139***	0.939	5.942***	0.120
Industry dummies	no		no		no		3-digit		no		no	
R-squared	0.662		0.671		0.675		0.726		0.689		0.671	
OP structural TFP ω									1			
1-year autocorrelation of OP residuals - "measurement error"									0.820			
Std.dev. of OP structural TFP ω									0.193			
# observations	1,843		1,678		1,678		1,678		969		969	

(1) Cobb Douglas - full sample

(2) Cobb Douglas - sample with no missing log college and log non college

(3) Similar to (2) but with labor split into college vs. non college

(4) Similar to (3), adds the log of firm age and 3 digit industry dummies as TFP controls. In a specification not shown, we add firm growth over the last 5 years as an extra control. The coefficients estimates and R-squared were very similar

(5) OP 3rd stage: estimation of log value added on log college, log non college, log capital, log firm age and OP structural TFP ω . See the text for more information.

OP 1st stage: the college and non college coefficients were retrieved by re-estimating (3) with a second-order polynomial in capital, investment and firm age

OP 2nd stage: nonlinear estimation of (log value added - 0.268*log college - 0.468*log non college) on capital, firm age and a polynomial in the estimate of unobserved productivity retreives the estimates of the coefficients on capital and firm age

(6) Similar to (3) but with the same sample as (5)

***/**/* reports significance at 1/5/10%

Table 5B - Labor Quality Augmented Production Function Estimates
Finance, Real Estate, R&D and Business Activities

Dep. variable: Log Value Added	(1) Baseline		(2) TFP controls		(3) OP		(4) Spec. (1) on OP sample	
	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.
Log labor	0.933***	0.022	0.883***	0.022	0.884***	0.029	0.928***	0.029
Log capital	0.095***	0.012	0.093***	0.013	0.082***	0.016	0.107***	0.017
Female	0.031	0.093	0.110	0.120	0.023	0.127	-0.060	0.114
College & master	1.163***	0.215	1.547***	0.318	1.139***	0.281	1.098***	0.266
Community college	0.477*	0.248	0.387	0.273	0.394	0.321	0.410	0.314
Vocational	1.134***	0.291	0.454**	0.231	1.136***	0.381	1.125***	0.364
Experience	0.136***	0.029	0.193***	0.045	0.180***	0.060	0.165***	0.052
Firm tenure 1 to 2 years	0.203	0.173	0.210	0.177	0.295	0.387	0.225	0.347
Firm tenure 3 to 5 years	0.002	0.179	0.038	0.188	-0.012	0.287	-0.121	0.256
Firm tenure 6 to 9 years	-0.456***	0.168	-0.326	0.207	-0.711***	0.210	-0.708***	0.201
Firm tenure 10 years and up	-0.418***	0.137	-0.323*	0.171	-0.455**	0.210	-0.534***	0.184
Industry tenure 1 to 2 years	0.490**	0.206	0.467**	0.208	0.514	0.490	0.535	0.467
Industry tenure 3 to 5 years	0.916***	0.257	0.767***	0.251	1.364**	0.545	1.447***	0.527
Industry tenure 6 to 9 years	0.639***	0.239	0.499**	0.237	1.074**	0.436	1.080***	0.419
Industry tenure 1o years and up	0.576***	0.196	0.222	0.185	0.760*	0.392	0.703*	0.364
Firm age (log)			-0.003	0.017	-0.023	0.020		
DH growth 5 years			-0.004	0.029				
Constant	3.494***	0.167	4.490***	0.222	5.406***	0.887	3.276***	0.241
Industry dummies	no		3-digit		no		no	
R-squared	0.727		0.761		0.747		0.732	
OP structural TFP ω					1			
1-year autocorrelation of OP residuals - "measurement error"					0.840			
Std.dev. of OP structural TFP ω					0.169			
# observations	1,678		1,678		969		969	

(1) Nonlinear estimation of a labor quality augmented Cobb Douglas production function

(2) Adds log of firm age, firm growth over the last 5 years and 3 digit industry dummies as TFP controls

(3) OP 3rd stage: estimation of log value added on log labor quality, log capital, log firm age and OP structural TFP ω. See in the text for more information. OP 1st stage: the labor and labor quality coefficients were retrieved by re-estimating (1) with a second-order polynomial in capital, investment and firm age. OP 2nd stage: nonlinear estimation of log value added minus labor quality on capital, firm age and a polynomial in the estimate of unobserved productivity retreives the estimates of the coefficients on capital and firm age

(4) Similar to (1) but with the same sample as (3)

***/**/* reports significance at 1/5/10%

Table 6A - Production Function Estimates - Machinery and Equipment

Dep. variable: Log Value Added	(1) Full sample		(2) Baseline		(3) College/non college		(4) TFP controls		(5) OP		(6) Spec. (3) on OP sample	
	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.
Log labor	0.904***	0.031	0.907***	0.033								
Log college					0.212***	0.027	0.213***	0.027	0.288***	0.031	0.274***	0.031
Log non college					0.675***	0.039	0.673***	0.039	0.606***	0.046	0.569***	0.047
Log capital	0.084***	0.021	0.078***	0.022	0.085***	0.022	0.081***	0.022	0.057**	0.026	0.091***	0.025
Firm age (log)							0.030	0.023	-0.015	0.026	0.038	0.025
Constant	5.362***	0.118	5.401***	0.123	5.981***	0.138	5.889***	0.183	3.665***	1.208	6.104***	0.171
R-squared	0.791		0.792		0.792		0.796		0.801		0.789	
OP structural TFP ω									1			
1-year autocorrelation of OP residuals - "measurement error"									0.800			
Std.dev. of OP structural TFP ω									0.133			
# observations	688		631		631		631		459		459	

(1) Cobb Douglas - full sample

(2) Cobb Douglas - sample with no missing log college and log non college

(3) Similar to (2) but with labor split into college vs. non college

(4) Similar to (3), adds the log of firm age, firm growth over the last 5 years and 3 digit industry dummies as TFP controls.

(5) OP 3rd stage: estimation of log value added on log college, log non college, log capital, log firm age and OP structural TFP ω . See the text for more information.

OP 1st stage: the college and non college coefficients were retrieved by re-estimating (3) with a second-order polynomial in capital, investment and firm age

OP 2nd stage: nonlinear estimation of (log value added - 0.268*log college - 0.468*log non college) on capital, firm age and a polynomial in the estimate of unobserved productivity retreives the estimates of the coefficients on capital and firm age

(6) Similar to (3) but with the same sample as (5)

***/**/* reports significance at 1/5/10%

Table 6B - Labor Quality Augmented Production Function Estimates
Machinery and Equipment

Dep. variable: Log Value Added	(1) Baseline		(2) OP	
	coef.	std. err.	coef.	std. err.
Log labor	0.881***	0.033	0.912***	0.043
Log capital	0.087***	0.022	0.113***	0.025
Female	0.540*	0.306	0.528	0.341
College & master	0.906**	0.386	1.859***	0.553
Community college	0.556	0.477	0.867	0.574
Vocational	1.225*	0.654	0.722	0.529
Experience	0.027	0.019	0.021	0.019
Firm tenure 1 to 2 years	0.712*	0.398	0.441	0.521
Firm tenure 3 to 5 years	0.697*	0.391	-0.157	0.406
Firm tenure 6 to 9 years	0.729*	0.380	0.023	0.425
Firm tenure 10 years and up	0.349	0.307	-0.112	0.395
Industry tenure 1 to 2 years	-0.478**	0.188	-0.354	0.350
Industry tenure 3 to 5 years	-0.194	0.266	-0.127	0.445
Industry tenure 6 to 9 years	-0.224	0.268	-0.022	0.459
Industry tenure 1o years and up	-0.448**	0.194	-0.193	0.390
Firm age (log)			0.119***	0.026
Constant	4.330***	0.322	2.599***	1.233
R-squared	0.804		0.812	
OP structural TFP ω			1	
1-year autocorrelation of OP residuals - "measurement error"			0.778	
Std.dev. of OP structural TFP ω			0.168	
# observations	631		459	

(1) Nonlinear estimation of a labor quality augmented Cobb Douglas production function

(2) OP 3rd stage: estimation of log value added on log labor quality, log capital, log firm age and OP structural TFP ω. See in the text for more information. OP 1st stage: the labor and labor quality coefficients were retrieved by re-estimating (1) with a second-order polynomial in capital, investment and firm age. OP 2nd stage: nonlinear estimation of log value added minus labor quality on capital, firm age and a polynomial in the estimate of unobserved productivity retreives the estimates of the coefficients on capital and firm age

***/**/* reports significance at 1/5/10%

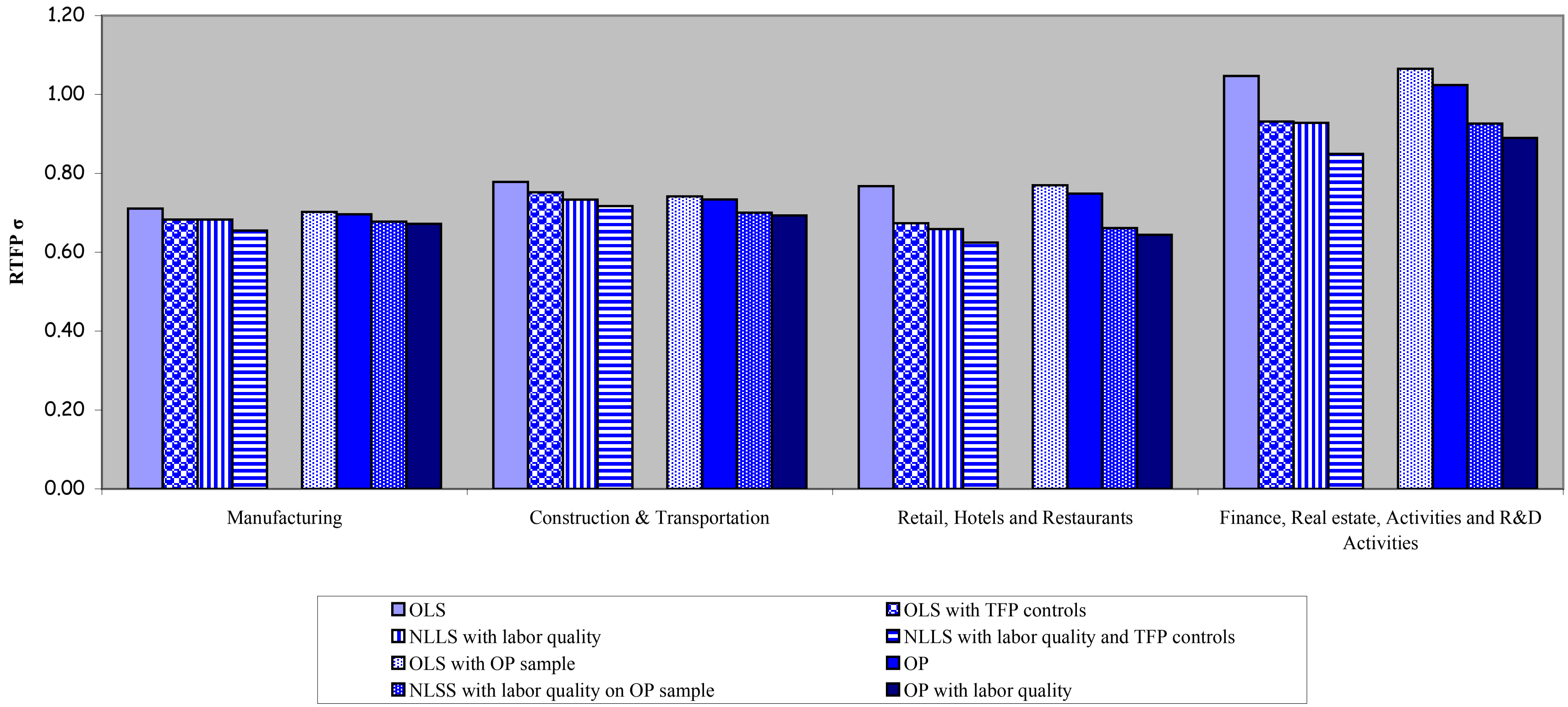
Table 7 - One Standard Deviation of Residual Total Factor Productivity in Multiples by Sector*

Sector	Baseline sample												OP sample											
	(1) OLS			(2) OLS with TFP controls			(3) NLLS with labor quality			(4) NLLS with labor quality and TFP controls			(5) OLS			(6) OP			(7) NLLS with labor quality			(8) OP with labor quality		
	Std.dev. log V.A.	R^2	RTFP σ	Std.dev. log V.A.	R^2	RTFP σ	Std.dev. log V.A.	R^2	RTFP σ	Std.dev. log V.A.	R^2	RTFP σ	Std.dev. log V.A.	R^2	RTFP σ	Std.dev. log V.A.	R^2	RTFP σ	Std.dev. log V.A.	R^2	RTFP σ	Std.dev. log V.A.	R^2	RTFP σ
Manufacturing	1.21	0.80	0.71	1.21	0.82	0.68	1.21	0.82	0.68	1.21	0.83	0.66	1.18	0.80	0.70	1.18	0.80	0.70	1.18	0.81	0.68	1.18	0.81	0.67
Construction & Transportation	0.99	0.66	0.78	0.99	0.68	0.75	0.99	0.69	0.73	0.99	0.70	0.72	0.96	0.66	0.74	0.96	0.67	0.73	0.96	0.69	0.70	0.96	0.70	0.69
Retail, Hotels and Restaurants	1.07	0.72	0.77	1.07	0.77	0.67	1.07	0.78	0.66	1.07	0.80	0.62	1.10	0.73	0.77	1.10	0.74	0.75	1.10	0.79	0.66	1.10	0.80	0.64
Finance, Real estate, Activities and R&D Activities	1.26	0.68	1.05	1.26	0.73	0.93	1.26	0.73	0.93	1.26	0.76	0.85	1.27	0.67	1.07	1.27	0.69	1.02	1.27	0.73	0.93	1.27	0.75	0.89

(1) Cobb Douglas OLS estimation
(2) Cobb Douglas OLS estimation with TFP controls
(3) Cobb Douglas NLLS estimation with labor quality
(4) Cobb Douglas NLLS estimation with labor quality and TFP controls
(5) OLS OP sample
(6) OP
(7) NLLS with labor quality on OP sample
(8) OP with labor quality

* The R-squared includes the OP structural productivity ω. σ is the difference in RTFP multiples for firms 1 standard deviation in log RTFP away. σ is calculated as exp(log standard deviation RTFP)-1. See the text for more information on how RTFP was constructed. Note that the sample size for the OP estimates is smaller because of missing data for investment

Figure 1 - One Standard Deviation of Residual Total Factor Productivity in Multiples by Sector*



* σ is the difference in RTFP multiples for firms 1 standard deviation in log RTFP away.
σ is calculated as exp(log standard deviation RTFP)-1. See in the text for more information on how RTFP was constructed. Note that the sample size for the OP estimates is smaller because of missing data for investment

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