Supplementary Web Appendix to

Smoothed LSDV Estimation of Functional-Coefficient Panel Data Models with Two-Way Fixed Effects

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Empirical Application

We showcase the practical usefulness of our two-way SLSDV estimator by revisiting the role of management for production. Researchers in business economics have long argued that management is an important intangible input to production contributing significantly to productivity differences across firms and, when aggregated, across countries. However, until recently, the data on systematic measurements of management practices have been lacking. The World Management Survey developed and since expanded by Bloom & Van Reenen (2007) and their coauthors was the major step forward in this regard, and the empirical management literature has ever since been growing.

In our empirical application, we revisit the estimation of management-augmented firm production functions from Bloom et al. (2017) that are aimed to measure the association between the firm's management practices and its production performance. Specifically, our point of departure is the (fully parametric) Cobb-Douglas specification akin to their baseline fixed-effects model:

$$y_{it} = \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 m_{it} + \mu_i + \lambda_t + u_{it}, \tag{A.1}$$

where y_{it} is the logged valued-added, k_{it} is the logged physical capital (fixed assets), l_{it} is the logged employment, and m_{it} is the logged management score.[1]

[1]We differ from Bloom et al.'s (2017) regression in that we log the management variable to facilitate the elasticity-like interpretation, exclude additional firm controls such as firm age and include year effects. We do so because we do not seek to "replicate" their analysis (for one, we do not have access to their data) but rather use their research as a context for illustrating our estimator. Also, adding the controls has little implication for our main results.

Table A.1. Data summary statistics

Variable	*Mean*	*Min*	*1st Qu.*	*Median*	*3rd Qu.*	*Max*
Value Added (Y)	249,942.1	25.9	28,945.0	67,806.5	183,019.9	16,067,545.7
Capital (K)	60,588.4	2.0	4,505.9	12,530.5	37,158.9	4,266,050.4
Labor (L)	880.3	4.0	159.8	271.0	631.2	65,682.0
Management (M)	3.06	1.06	2.67	3.06	3.47	4.86

Value added and the tangible fixed assets (capital) are in USD; labor is the number of employees; management score is the average of 18 management questions.

Our focus is on relaxing the time-invariance of production technology and, specifically, of the relationship between management and firm output implicitly assumed in (A.1). It is only natural to expect the role of management practices for firm production to change over time due to both the technological and institutional changes. We therefore let the input elasticities, including that corresponding to the managerial input, smoothly vary with (discretized) time in an unspecified way. By letting the production-function coefficients vary with time in an arbitrary nonparametric fashion, we are able to accommodate potential temporal variation in the relationship between management and output in a flexible way that is robust to misspecification. Thus, our preferred production function is a semiparametric functional-coefficient two-way fixed-effects model:

$$y_{it} = \beta_1(D_t)k_{it} + \beta_2(D_t)l_{it} + \beta_3(D_t)m_{it} + \mu_i + \lambda_t + u_{it}, \tag{A.2}$$

where the functional coefficient vector $\boldsymbol{\beta}(\cdot) = (\beta_1(\cdot), \beta_2(\cdot)', \beta_3(\cdot)')'$ is a function of a (scalar) ordered *discrete* time variable D_t taking on T different values in $\{1, 2, \ldots, T\}$ with T being small. We opt to discretize time as opposed to treating it continuously by defining $D_t = t/T$ as commonly done in the semi/nonparametric literature on nonstationary processes (e.g., Zhang & Wu, 2012) mainly because most empirical applications in microeconomics deal with short annual panels implying that $n \gg T$ with the measurement of time (years) being clearly discrete. Our data are exactly that, which also helps keep the illustration of our estimator as relevant for such applications as possible. For more comfort, one may choose to think of D_t not as the "time" index but, say, as a normalized proxy/measure of the global technological stock shareable by all owing to its non-rivalry and low excludability. For other examples of a categorical treatment of the smoothing time variable in the context of production function estimation, also see Dewitte et al. (2020). A discrete treatment of D_t also has the secondary benefit of having no adverse impact on the convergence rate of the estimator.

Since the smoothing variable D_t is not continuous, equation (A.2) is estimated via the local-*constant* version of our proposed two-way SLSDV estimator using the AICc-optimal bandwidth and Li & Racine's (2007) kernel function for ordered discrete variables.

By virtue of treating time as an *ordered* "factor" variable entering nonparametric functional

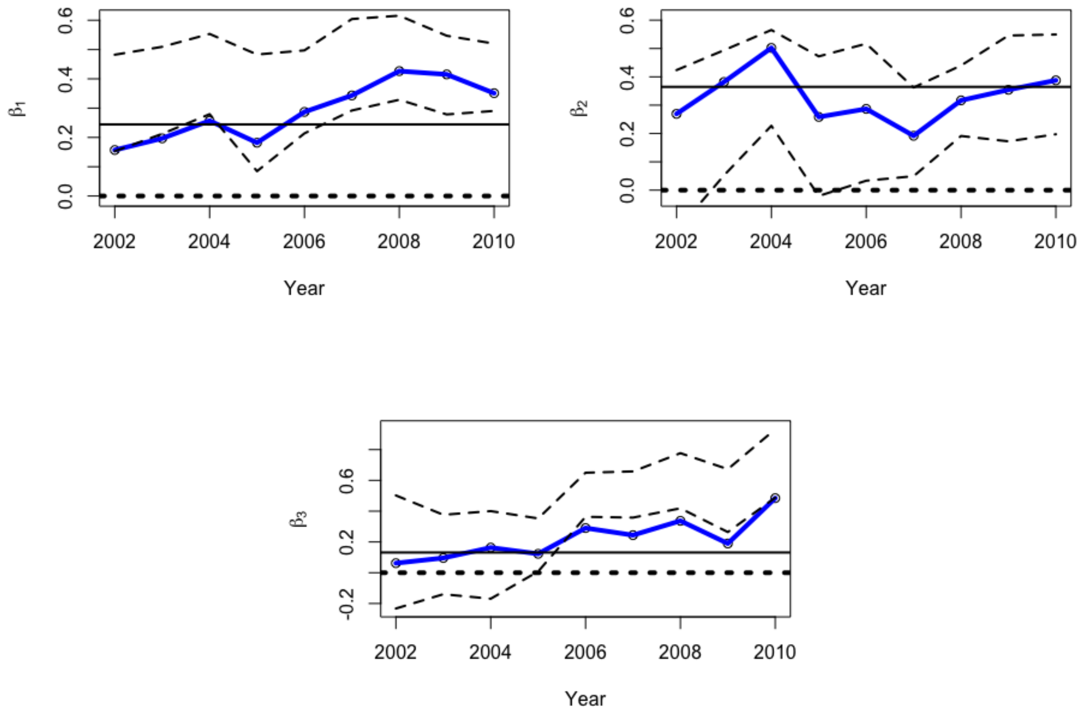

Figure A.1. Semiparametric input elasticity estimates over the years [the management elasticity of interest $\widehat{\beta}_3(D_t)$ is in bottom plot]

coefficients, we essentially achieve the estimation of a fully saturated flexible model (with a complete set of time dummies) without the need to actually cell-split the sample based on years. By relying on recent advancements in the kernel estimation of functional-coefficient models with exclusively discrete smoothing variables (see Li et al., 2013), we circumvent the need for time dummies and, further, can use relevant information from "similar" time periods (from before and after) during estimation of the coefficients for each time period by "smoothing" them over time. Not least importantly, such a kernel-based nonparametric treatment of a scalar time variable comes at no cost in terms of the speed of convergence since smoothing over categorical variables does not contribute to the "curse of dimensionality." In the absence of continuous smoothing variables (like in our case), the estimator of unknown coefficients exhibits a parametric rate.

We use the publicly available 2002–2010 ($T = 9$) combined survey data from across twelve countries used in Bloom et al. (2012) that contain repeatedly measured company accounts information. The sample includes $n = 1,345$ firms. The data are summarized in Table A.1. We refer the reader to the World Management Survey website for the details on data. The output and input variables are demeaned prior to the estimation to better fit the intercept-free specification.

Figure A.1 summarizes year-specific estimates of the three functional coefficients from the semiparametric management-augmented production function in (A.2) plotted along with their fixed-

Table A.2. Semiparametric estimates of the management elasticity

Year	*Estimate*	*Lower Bound*	*Upper Bound*
2002	0.0621	–0.2327	0.5022
2003	0.0957	–0.1397	0.3764
2004	0.1633	–0.1690	0.4003
2005	0.1227	0.0081	0.3527
2006	0.2903	0.3632	0.6498
2007	0.2441	0.3581	0.6581
2008	0.3372	0.4184	0.7767
2009	0.1898	0.2641	0.6728
2010	0.4846	0.4876	0.9321

Bounds for the accelerated bias-corrected bootstrap intervals are at the 95% confidence.

coefficient counterparts (solid horizontal lines) from a fully parametric model in (A.1) for comparison. In the figure, each point estimate of $\boldsymbol{\beta}(D_t)$ is accompanied by the corresponding 95% accelerated bias-corrected bootstrap confidence intervals (dashed lines) which are second-order accurate and provide means not only to correct for the estimator's finite-sample bias but also to account for higher-order moments (particularly, skewness) in the sampling distribution.[2]

Our interest is in the management elasticity $\beta_3(D_t)$. Overall, the data point to non-negligible temporal heterogeneity in the relationship between the firm's management practices and its production performance. The semiparametric estimates of the management elasticity are statistically significant in the year 2005 onward and suggest a growing importance of the managerial input for production over time (also see Table A.2). Contrasting these estimates with the fixed-coefficient counterpart of the more modest effect size (0.13), we see that, in the face of technological and institutional changes, a time-invariant specification can underestimate the contribution of management to production thereby leading to incomplete, if not distorted, insights into the role of management practices for firm performance. This highlights the practical importance of using more flexible specifications.

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[2]Note that, given these "corrections," the point estimates may sometimes lie outside the confidence interval.

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