Heterogeneous Capital and the Productivity of UK Manufacturing Firms

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Abstract

This paper explores how investment in different types of capital affects estimates of firm level total factor productivity (TFP) growth in the UK. We find that taking account separately of firms' investments in intangible as well as tangible assets, and of costs of adjustment between their fixed and variable cost inputs, TFP growth within UK manufacturing firms slows only moderately, rather than exhibiting the striking slowdown reported in the prior literature. This is because the standard approach, which assumes homogeneity in capital inputs when estimating firm-level TFP, tends to overstate the revenue and implied output elasticities, thereby understating TFP. Firms' adjustment costs in both tangible and intangible inputs also affect their variable costs, which in turn influence the identification of revenue and output elasticities, further distorting TFP estimates.

1. Introduction

The persistent slowdown in UK productivity during the past 20 years has prompted much debate, with a growing consensus that firm-level total factor productivity (TFP) is central to understanding the problem (Jacob and Mion, 2023; Coyle, McHale, Bournakis, and Mei, 2024; Goldin, Koutroumpis, Lafond, and Winkler, 2024). A large literature has investigated drivers of productivity growth, emphasizing intangible capital (Haskell and Westlake, 2020), the diffusion of digital technologies (Coyle, Lind, Nguyen, and Tong, 2022; Brynjolfsson, Li, and Raymond, 2025), and measurement challenges in constructing capital stock and services (Groth, Gutierrez-Domenech, and Srinivasan, 2004). Other contributions highlight labour costs, economies of scale, and systematic errors in measuring inputs and outputs at the firm level (Basu and Fernald, 2000; Autor, Dorn, Katz, Patterson, and Reenen, 2017; Atalay, Hortaçsu, Kimmel, and Syverson, 2025).

Despite these insights, much of the existing empirical work rests on a standard framework that assumes capital inputs are homogeneous. In practice, however, capital is heterogeneous: it encompasses tangible assets (land, buildings, machinery, equipment) and intangible assets (R&D, software, data, management systems, workforce training, brand value). Treating such diverse inputs as uniform overlooks two crucial points. First, some forms of capital are subject to adjustment costs, while others behave as fixed factors that do not vary with output. Second, ignoring these distinctions will bias the estimation of revenue elasticities and returns to scale, and thus the residual measure of TFP. In periods of high investment, firms may temporarily divert resources to installation or reallocation, lowering measured output and generating downward-biased productivity estimates.

Coyle et al. (2024), for example, estimate output elasticities using a revenue function and find a steep decline of 13-18% in within-firm manufacturing TFP between 2008 and 2019; but they abstract from firms' investment choices between tangible and intangible services. Other studies rely on accounting measures of tangible fixed assets as proxies for capital (Harris and Moffat, 2017; Harris and Moffat, 2019; Gibbon and Schain, 2023; Jacob and Mion, 2023), again neglecting the heterogeneity of capital inputs.

Yet the composition of investment has shifted toward intangibles, weakening the responsiveness of tangible investment to standard explanatory variables (Gutiérrez and Philippon, 2016). Other evidence highlights the issue: Díaz and Franjo (2016) attribute low Spanish TFP growth to inefficient allocation of investment between technological and residential capital. Ignoring such distinctions can inflate measured dispersion in TFP (Mason, O'Mahony and Riley, 2018; Martin and Riley, 2025) and distort the relationship between firm-level innovation and aggregate growth (De Ridder, 2024).

Figures 1 and 2 highlight why capital heterogeneity matters in the UK context. Figure 1 shows a marked shift from tangible to intangible assets between 2001 and 2015, consistent with evidence from van Ark, de Vries, and Erumban (2023) of declining tangible investment and rising intangible investment across advanced economies following the Global Financial Crisis. Figure 2 shows the distribution of firm-level capital composition within two-digit manufacturing industries. Intangible investment is highly skewed within many industries, with a small number of firms holding disproportionately large software and database assets, while tangible capital – particularly land and buildings – exhibits a more even distribution across firms. These patterns highlight the importance of distinguishing capital types when analysing firms' investment behaviour and productivity.

Why might capital heterogeneity and adjustment costs make a material difference in our understanding of UK manufacturing TFP estimates and its growth trends? First, cross-country studies on the sources of economic growth demonstrate that intangible capital contributes between one-fifth and one-third of labour productivity growth in the market sector of advanced economies (Marrano, Haskel, and Wallis, 2009; Corrado, Hulten, and Sichel, 2009; van Ark, Hao, Corrado, and Hulten, 2009; Corrado, Haskel, Jona-Lasinio, and Iommi, 2013), while Corrado, Haskel, and Jona-Lasinio (2017) find evidence of productivity spillovers associated with increases in intangible capital. During the 2010s, the UK economy became increasingly intangible-intensive, with growing investment in digital technologies, data services, and knowledge-based assets. These forms of capital are characterised by high upfront costs, uncertain payoffs, and limited representation in conventional capital statistics.[1] Consequently, as firms reallocate

[1] Evidence indicates that UK investment in intangible assets has exceeded investment in tangible assets since the early 2000s. In 2014, intangible investment amounted to £133 billion, compared with £121 billion in tangible investment – around 9 % higher. Within this total, firm expenditure on training accounted for £26 billion, organisational capital for £22 billion, design for £14 billion, software for £28 billion, branding for £15 billion, and scientific R&D for £19 billion. A comprehensive and detailed account of these estimates can be found in the report by Goodridge, Haskel, and Wallis (2016) published by the UK Intellectual property Office. In addition, the ONS launched a firm-level survey of intangible investment in 2009, with results published in July 2010. This Investment in Intangible Assets Survey covered 2,004 UK private sector firms with ten or more employees in both production and service industries and documented a substantial level of spending across a wide range of intangible asset categories. For further details, see Awano, Franklin, Haskel, and Kastrinaki (2010).

resources from tangible to intangible accumulation, traditionally measured TFP growth may appear to slow even as underlying productive capacity improves.

Second, the reallocation of resources toward intangible assets is not frictionless. Unlike tangible capital, intangible investment typically entails higher fixed and variable adjustment costs. As highlighted by Cooper, Haltiwanger, and Willis (2006) and Bloom, Bond, and Van Reenen (2007), such investment can be viewed as a partially irreversible process in which uncertainty dampens firms' short-run responses to demand shocks. In the case of intangibles, fixed adjustment costs arise from establishing new organisational processes, retraining staff, and building digital infrastructure – activities that require substantial upfront commitment before yielding returns. Variable adjustment costs, such as system integration, software maintenance, and data management, necessitate continuous investment and can temporarily depress measured output.

Taken together, these suggest that the UK "productivity puzzle" may partly stem from the inadequacy of traditional TFP accounting frameworks to capture intangibles-driven growth.

This paper incorporates capital heterogeneity and adjustment costs into the measurement of TFP in UK manufacturing. Using the Annual Respondents Database X (ARDx),[2] which provides detailed data on firms' investments in land and buildings, software and databases, and other assets over 1997-2020, we reconstruct firm-level TFP measures that account explicitly for differences across capital types and for the role of fixed versus variable inputs. Following Autor et al. (2017), we incorporate adjustment costs by embedding fixed components of labour and capital into the revenue function,

[2] The ARDx database – constructed by integrating the Annual Respondents Database (ARD) and the Annual Business Survey (ABS) – is provided and maintained by the Virtual Microdata Library (VML) team at the Office for National Statistics (ONS). In the current ARDx system, capital stocks are constructed using the ONS Perpetual Inventory Method (PIM) with the official ONS parameter files. Service lives are not fixed at annual depreciation but instead follow the detailed "asset" × "industry service-life" assumptions provided in the ONS PIM input file (ONS Perpetual Inventory Method Inputs). The AverageLifeLengths worksheet lists the operative service lives (in quarters) for all assets – e.g., dwellings have a service life of two hundred quarters, which is equal to fifty years; other buildings have approximately one hundred and fifty-four quarters, which is roughly thirty-eight years on average; transport equipment has approximately fifty-two quarters, which is about thirteen years; and machinery has approximately seventy-one quarters, which is about eighteen years, and intangible assets such as software and databases have twenty quarters (five years). Depreciation is applied using the ONS's age-efficiency and retirement profiles (specified in "Dep_ret_profiles" column). This reflects the post-Blue Book PIM framework now used to produce the official UK capital stock statistics. While Kauma and Mion (2024) developed a comprehensive firm-level dataset combining ARD, ABS, and FAME, and we acknowledge its broader firm-year coverage through 2004-2017, their dataset is primarily suited to analyses of geographical variation. By contrast, our study focuses on trends in heterogeneous capital investment over the period 1997–2020, for which the ARDx database offers the most appropriate foundation.

allowing us to capture the bias that arises when reallocation and installation activities temporarily depress output.

Our contribution is twofold. First, we extend the standard TFP framework by distinguishing heterogeneous forms of capital – tangible and intangible – and by accounting for fixed and variable components in production. This corrects the biases that arise when capital heterogeneity and adjustment costs are ignored. Second, using the ARDx dataset, we show that once these elements are incorporated, within-firm TFP growth in UK manufacturing appears broadly flat since 2008, rather than experiencing the dramatic slowdown suggested by prior estimates. Recognising the contribution of intangible assets indicates that UK manufacturing firms' post-GFC productivity has been more resilient than headline figures imply.

Finally, while our results indicate that the slowdown in within-firm TFP is milder than commonly reported, this does not contradict the well-documented stagnation of labour productivity in UK manufacturing since the mid-2000s. A natural interpretation is that weak capital deepening and subdued investment – particularly in machinery, equipment, and other tangible assets – have played an increasingly important role in shaping aggregate productivity outcomes (Goodridge and Haskel, 2023; Alayande and Coyle, 2023; Patton, 2025; Chadha and Samiri, 2026). Our framework, by capturing firms' reallocation between tangible and intangible capital, provides complementary evidence for this investment channel and aligns with the broader discussion that insufficient investment remains a key contributor to the UK productivity puzzle.

The rest of the paper is organized as follows: Section 2 outlines our structural model and estimation framework. Section 3 describes the ARDx data and highlights capital heterogeneity across UK manufacturing. Section 4 presents the main results. Section 5 concludes.

2. Structural Approach and Estimation Framework

2.1 The Quality Adjusted TFP Model

In this section, we first set out briefly the structural model outlined in Coyle et al. (2024) and Coyle, Bournakis, and Mei (2025) as a benchmark before introducing capital heterogeneity and adjustment costs.

Firm-level demand. We start with a representative consumer with a Constant Elasticity of Substitution (CES) utility function of the quality-adjusted goods produced by the N firms in the industry, as in Melitz (2000):

$$U_t\left(\left(\left[\sum_{i=1}^{N}\left(\Lambda_{ijt}\mathrm{Q}_{ijt}\right)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}\right), Z_t\right), \tag{1}$$

where Z_t represents aggregate industry demand shifter, Λ_{ijt} is a measure of the quality of the good produced by firm i sector j at time t (where quality improvements result from changes in product characteristics that are valued by consumers), Q_{ijt} is the volume output produced by firm i sector j at time t, and η captures the elasticity of substitution between the N goods in the output index.

We incorporate both a representative consumer with a preference for variety, and vertical differentiation based on quality between products that enter the industry output index. We denote quality-adjusted output as $Q^{*}_{ijt} = \eta_{jt}\mathrm{Q}_{ijt}$. We assume that $\eta > 1$ and that each firm produces a single product variety. Given the allocation of income to manufacturing goods, the demand function facing a given firm producing a good with quality Λ_{ijt} is derived as:

$$Q_{ijt} = \Lambda_{ijt}^{\eta-1}\left(\frac{P_{ijt}}{P_{jt}}\right)^{-\eta}\frac{\alpha P_t Y_t}{P_{jt}} \tag{2}$$

where α represents the proportion of income the representative consumer allocates to manufacturing goods (i.e., $P_{Zt}Z_t = \alpha P_t Y_t$ for manufacturing goods and $P_{Xt}X_t = (1-\alpha)$ $P_t Y_t$ for others), and the price index for the industry, P_{jt}, is given by:

$$P_{jt} = \left[\sum_{i=1}^{N}\left(\frac{P_{ijt}}{P_{jt}}\right)^{\eta-1}\right]^{\frac{1}{\eta-1}} \tag{3}$$

Eq. (3) implies that quality improvements (Λ_{ijt}) are reflected in a lower industry price index. Moreover, a change in a particular good's Λ_{ijt}captures relative as well as absolute changes in quality (Fisher, 1965; Hulten, 1992; Coyle et al., 2024).

Firm production function. Turning to production side of the economy, we assume each firm has the Cobb-Douglas production function:

$$Q_{ijt} = \Omega_{ijt} L_{ijt}^{\beta_l} K_{ijt}^{\beta_k} M_{ijt}^{\beta_m} \tag{4}$$

where Ω_{ijt} is a (firm-specific) measure of Hicks-neutral technical change, L_{ijt} is labour, K_{ijt} is fixed capital, and L_{ijt} is materials.

Firm revenue function. To derive the revenue function, it is useful to write the demand function (5) in inverse form as:

$$\frac{P_{ijt}}{P_{jt}} = \Lambda_{ijt}^{\frac{\eta-1}{\eta}} Q_{ijt}^{-\frac{1}{\eta}} \frac{\alpha P_t Y_t}{P_{jt}}. \tag{5}$$

where the quality adjustment factor, Λ_{ijt}, is a shift factor for the inverse demand function that can reflect changes in quality corresponding to changes in the representative consumer's marginal willingness to pay. Using (4) and (5), total deflated firm revenue is:

$$\frac{R_{ijt}}{P_{jt}} = \left(\Lambda_{ijt} Q_{ijt}\right)^{\frac{\eta-1}{\eta}} L_{ijt}^{\beta_l\left(\frac{\eta-1}{\eta}\right)} K_{ijt}^{\beta_k\left(\frac{\eta-1}{\eta}\right)} M_{ijt}^{\beta_m\left(\frac{\eta-1}{\eta}\right)} \left(\frac{R_{jt}}{P_{jt}}\right)^{\frac{1}{\eta}}, \tag{6}$$

where industry revenue is $R_{jt} = P_{jt} Z_t = \alpha P_t Y_t$ and firm-level revenue is $R_{ijt} = P_{ijt} Q_{ijt}$.

TFPQ* measures. Taking natural logs of (6) and rearranging we obtain:

$$r_{ijt} - p_{jt} = \frac{1}{\eta}\left(r_{jt} - p_{jt}\right) + \frac{(\eta-1)\beta_l}{\eta} l_{ijt} + \frac{(\eta-1)\beta_k}{\eta} k_{ijt} + \frac{(\eta-1)\beta_m}{\eta} m_{ijt} + \frac{\eta-1}{\eta}\left(\lambda_{ijt} + \omega_{ijt}\right), \tag{7}$$

where lower case letters represent the natural log of a variable. A critical feature of (7) is that the identification of η is possible from the coefficient on the deflated-industry-revenue variable in the estimated revenue equation (Klette and Griliches, 1996). Hence, Eq. (7) is used to estimate revenue function parameters. We then derive our natural log of TFPQ* as:

$$\left(\lambda_{ijt} + \omega_{ijt}\right)^{*} = \frac{\eta}{\eta-1}\Psi_{ijt} - \frac{1}{\eta-1}\left(r_{jt} - p_{jt}\right). \quad (8)$$

where $\Psi_{ijt} = r_{ijt} - p_{jt} - \left(\frac{(\eta-1)\beta_l}{\eta} l_{ijt} + \frac{(\eta-1)\beta_k}{\eta} k_{ijt} + \frac{(\eta-1)\beta_m}{\eta} m_{ijt}\right)$ is defined as revenue-based total factor productivity, and $\left(\lambda_{ijt} + \omega_{ijt}\right)^{*}$ is our key measure – the TFPQ* (i.e., quality-adjusted total factor productivity). Note that with revenue data alone it will be impossible to separately identify the effects of λ_{ijt} (quality adjustment factor) and ϖ_{ijt} (physical productivity).

Heterogeneous Capital. From Eq. (4), we now introduce three types of capital stock – land and buildings, databases and software, and others. The Cobb-Douglas production function outlined in Eq. (4) can then be extended as:

$$Q_{ijt} = \Omega_{ijt}\ L_{ijt}^{\beta_l}\ \underbrace{KB_{ijt}^{\beta_{KB}}}_{\textbf{Land \& Building}}\ \underbrace{KS_{ijt}^{\beta_{KS}}}_{\textbf{Software \& Database}}\ \underbrace{KO_{ijt}^{\beta_{kO}}}_{\textbf{Others}}\ M_{ijt}^{\beta_m} \quad (9)$$

where KB_{ijt} is capital in land and building, KS_{ijt} is capital in software and database, and KO_{ijt} is others. Rearranging parameters in (7) we obtain an extended version of the estimation model

$$r_{ijt} - p_{jt} = \frac{1}{\eta}\left(r_{jt} - p_{jt}\right) + \frac{(\eta-1)\beta_l}{\eta} l_{ijt} + \frac{(\eta-1)\beta_{kB}}{\eta} kB_{ijt} + \frac{(\eta-1)\beta_{kS}}{\eta} kS_{ijt} + \frac{(\eta-1)\beta_{kO}}{\eta} kO_{ijt} + \frac{(\eta-1)\beta_m}{\eta} m_{ijt} + \frac{\eta-1}{\eta}\left(\lambda_{ijt} + \omega_{ijt}\right), \quad (10)$$

We can derive TFPQ*K with heterogeneous capital stock as:

$$\left(\lambda_{ijt} + \omega_{ijt}\right)^{*K} = \frac{\eta}{\eta-1}\Psi_{ijt}^{k} - \frac{1}{\eta-1}\left(r_{jt} - p_{jt}\right). \quad (11)$$

where $\Psi_{ijt}^{k} = r_{ijt} - p_{jt} - \left(\frac{(\eta-1)\beta_l}{\eta} l_{ijt} + \frac{(\eta-1)\beta_{kB}}{\eta} kB_{ijt} + \frac{(\eta-1)\beta_{kS}}{\eta} kS_{ijt} + \frac{(\eta-1)\beta_{kO}}{\eta} kO_{ijt} + \frac{(\eta-1)\beta_m}{\eta} m_{ijt}\right)$ is a revenue-based measure of total factor productivity that accounts for heterogeneity in capital across firms. The term $(\lambda_{ijt} + \omega_{ijt})^{*K}$ is our key derivative from the model, accounting for heterogeneous capital.

Fixed and Variable Inputs and Adjustment Costs – TFPQ*KV. In identifying TFPQ* and TFPQ*K from estimating the baseline revenue model, we assume that all inputs enter as variable factors in the production function. Nonetheless, in a more realistic setting, explanations of key trends – such as the declining labour share of income (Autor et al., 2020) and the rising importance of intangible capital (Haskell and Westlake, 2020) – point to the central role of fixed factors and the economies of scale they create. These elements are also critical for measuring TFP accurately, since overlooking fixed inputs can distort revenue elasticities and bias productivity estimates.

Some inputs are subject to adjustment frictions, such as capital adjustment costs, or hiring/firing costs for labour. At the same time, a share of a firm's labour force and capital may be involved in product design or administrative activities, where the costs of these "intangible investments" do not vary with output. Ignoring these fixed factors would bias our estimates of the share of revenue variability attributable to changes in input use, and, consequently, distort our inference regarding the evolution of TFP.

To augment our baseline model with fixed inputs, we assume that the amount of the fixed factor is common across firms for industry j in year t. For expositional simplicity, we assume that capital and labour both have fixed components.

Variable labour is denoted V_{it} and fixed labour is denoted F_t, so that $L_{it} = V_{it} + F_t$. Under monopolistic competition and specific elasticity of substitution in industry j, labour share in total revenue is expressed as (Autor et al. 2017):

$$s_{it}^{L} = \frac{w_{it}L_i}{P_{it}Q_{it}} = \frac{w_{it}\left(V_{it}^{l}+F_t^{l}\right)}{P_{it}Q_{it}}$$
$$= \underbrace{\frac{\beta_l}{\mu}}_{\textbf{Constant}} + \underbrace{F_t^{l}}_{\textbf{Fixed Factor}} \underbrace{\frac{w_{it}}{P_{it}Q_{it}}}_{\textbf{Wage Ratio}} . \tag{12}$$

Eq. (12) implies that in industry j in year, it is possible to estimate the size of the fixed labour factor from a regression of the labour share of total revenue s_{it}^{L} on a constant term $\frac{\beta_l}{\mu}$ (assuming the output elasticity of labour β_l and the mark-up μ are both constant) and the ratio of the wage to firm revenue $\frac{w_{it}}{P_{it}Q_{it}}$. Note that here we allow the wage to be firm specific given likely differences in the composition of labour force across firms, so that the average wage is calculated as the wage bill divided the number of employees in the firm. The fixed factor F_t^l is then the coefficient on the ratio of the wage to firm revenue variable.

An analogous framework is required for fixed capital:

$$s_{it}^K = \frac{r_{it}K_i}{P_{it}Q_{it}} = \frac{r_{it}\left(V_{it}^k + F_t^k\right)}{P_{it}Q_{it}}$$
$$= \underbrace{\frac{\beta_k}{\mu}}_{\textbf{Constant}} + \underbrace{F_t^k}_{\textbf{Fixed Factor}} \underbrace{\frac{r_{it}}{P_{it}Q_{it}}}_{\textbf{Capital Ratio}} . \quad (13)$$

Eq. (13), similarly, implies that we can estimate the size of the fixed capital factor from a bivariate regression of the capital share of total revenue s_{it}^K on a constant $\frac{\beta_k}{\mu}$ (with assumption that the output elasticity of capital β_k and the mark-up μ are both constant) and the ratio of the capital to firm revenue $\frac{r_{it}}{P_{it}Q_{it}}$. Again, we allow the capital price to be firm specific given likely differences in the composition of firm labour forces. The average capital price is then calculated as the capital costs divided employment in the firm. We can then obtain the fixed factor as the coefficient on the ratio of the capital to firm revenue variable in Eq. (13).

With these implied industry and year specific fixed factors, we subtract the fixed factors from total usage to get the implied variable factor usage for each industry in each time period. Importantly, since we distinguish buildings/land, software/databases, and other capitals, we can also subtract the fixed component from these capital inputs. The inferred variable factors in labour and capital inputs can then replace total factor usage in our estimation of the revenue function. To the extent that such fixed factors represent investments in activities such as improved product design and (or) improved firm-level organisation – highlighted in the intangible investment literature – they are expected to influence the derived measures of TFP.

2.2 Estimation Strategy

The parameters of interest include the elasticity of substitution $1/\eta$, revenue elasticity ($\frac{(\eta-1)\beta_l}{\eta}$, $\frac{(\eta-1)\beta_{kB}}{\eta}$, $\frac{(\eta-1)\beta_{kS}}{\eta}$, $\frac{(\eta-1)\beta_{kO}}{\eta}$, and $\frac{(\eta-1)\beta_m}{\eta}$), implied output elasticity $(\beta_l, \beta_{kB}, \beta_{kS}, \beta_{kO}, \beta_m)$, and firm-level TFP. To obtain these estimates, we follow Blundell and Bond (1998) and Blundell and Bond (2000), which account for adjustment costs in all inputs and serially correlated productivity shocks (i.e., $\lambda_{ijt} + \varpi_{ijt}$) following an AR(1) process, as well as unobserved heterogeneity in $\lambda_{ijt} + \varpi_{ijt}$ across firms. In addition to adjustment costs, we allow input choices to respond to contemporaneous productivity shocks. This introduces the common challenges of unobserved heterogeneity and simultaneity in estimating the revenue function (Griliches and Mairesse, 1995).

Following Coyle et al. (2024) and Coyle, Bournakis, and Mei (2025), we begin with a specification that addresses both corrections and set $\pi_{ijt} = \frac{\eta_j-1}{\eta_j}(\lambda_{ijt} + \omega_{ijt})$ and assume

$$\pi_{ijt} = \pi_{it} + \upsilon_{ijt}, \tag{15}$$

and

$$\upsilon_{ijt} = \rho_j \upsilon_{ij(t-1)} + \xi_{ijt}. \tag{16}$$

where ξ_{ijt} is a zero mean random shock that is potentially correlated with input choices, and we assume $0 < |\rho_j| < 1$. Lagging (10) by one period, multiplying the resulting equation through by ρ_j, and subtracting the result from (10), gives the quasi-differenced equation:

$$\begin{aligned} r_{ijt} - p_{jt} = {} & \rho_j\left(r_{ij(t-1)} - p_{j(t-1)}\right) + \frac{1}{\eta_j}\left(r_{jt} - p_{jt}\right) - \rho_j\left(r_{j(t-1)} - p_{j(t-1)}\right) \\ & + \frac{(\eta-1)\beta_l}{\eta}\left(\tilde{l}_{ijt} - \rho_j \tilde{l}_{ij(t-1)}\right) + \frac{(\eta-1)\beta_{kB}}{\eta}\left(\widetilde{kB}_{ijt} - \rho_j \widetilde{kB}_{ij(t-1)}\right) \\ & + \frac{(\eta-1)\beta_{kS}}{\eta}\left(\widetilde{kS}_{ijt} - \rho_j \widetilde{kS}_{ij(t-1)}\right) + \frac{(\eta-1)\beta_{kO}}{\eta}\left(\widetilde{kO}_{ijt} - \rho_j \widetilde{kO}_{ij(t-1)}\right) \\ & + \frac{(\eta-1)\beta_m}{\eta}\left(\widetilde{m}_{ijt} - \rho_j m_{ij(t-1)}\right) + \left(1-\rho_j\right)\pi_{ijt} + \xi_{ijt}, \end{aligned} \tag{17}$$

The firm fixed effect induces a correlation between the lagged dependent variable and the error term ξ_{ijt} (Nickell, 1981). Additionally, input variables in the revenue equation may become correlated with the error term due to immediate input responses to productivity shocks. One way to estimate Eq. (17) consistently is to use first differences with instrumental variables for potentially endogenous regressors. Blundell and Bond (1998) and Blundell and Bond (2000) propose mild initial conditions that allow lagged levels of endogenous variables to serve as valid instruments for first differences. However, they note that these lagged levels can be weak instruments in production function estimation. As an alternative, they recommend using System GMM, which estimates the model in both first differences and levels. Under certain conditions, lagged first differences serve as valid instruments for the levels equation, and System GMM typically provides more efficient estimates than a single-equation approach. We apply this method to estimate the parameters of the revenue function.

3. Data

We use Office for National Statistics' Annual Business Inquiry (1997–2007), Annual Business Survey (2008–2020), Annual Respondents Database x (ARDx), building a panel of firms spanning through 1997-2020. The ARDx is the largest business survey database for the UK and has been employed by many UK productivity researchers including Riley, Bondibene, and Young (2014), Barnett et al. (2014), Harris and Moffat (2017), as well as Jacob and Mion (2023). We merge these datasets to combine variables across the period 1997–2020.

We adopt ARDx capital stock variables created and maintained by the Virtual Microdata Library (VML) team at ONS, in which the variables are constructed using Perpetual Inventory Model (PIM):

$$K_{ijt} = K_{ijt-1}\left(1 - \delta_j\right) + I_{ijt}. \tag{14}$$

where δ_j is the industry-specific deprecation rate, K_{ijt} is the capital stock of firm i in period t and $t-1$, and I_{ijt} is the (net) investment level of firm i in period t. Capital stock is constructed separately for each asset type. As evident from the equation, the PIM requires both initial capital stock and investment data.[3] While the underlying program for capital stock construction can be adjusted – for example, to reflect specific choices regarding depreciation rates or real versus nominal prices – we directly adopt the version provided in ARDx. This ensures that any observed differences in productivity trends cannot be attributed to systematic differences in our construction of the capital stock variable.

To build the dataset, we implement the lowest unit – reporting unit (or the observation unit) – in the data. Throughout the paper, we refer these units as firms.[4] Building on Coyle and Mei (2023) and Coyle et al. (2024), we focus on firms in manufacturing industry, which has been identified as one of the biggest contributions to the UK slow growth in productivity. This gives us twenty-three sectors within the manufacturing industry, with 208,661 observations throughout the period 1997-2020. For each firm, there are data on total revenue, total employment, capital stock and purchases of inputs. As all monetary values are in nominal terms, we employ the ONS 2-digit industry-level producer output price deflator (Jan-Mar 1997 to Apr-Jun 2024)[5] and input price indices (manufacturing PPI)[6] to deflate the nominal values to 2022 prices (as reference year, in £ thousand).

[3] There are, however, issues with the estimation and allocation of the initial level of capital stock and missing investment data. First, to deal with the missing investment data, the VML team employs a rate of investment-per-employee based across all observed investment and employment (taken from IDBR). The reason for the choice of employment as the weight is because employment variable is always observed in all report units for all years. The missing investment data is then replaced by using the product between the investment-per-employee rate and the employment. For the initial capital stock, second, the initial process is that the first time a reporting unit is observed it is then given an initial capital stock, calculated as a proportion of the total capital stock in that year. However, this process ignores all firm and industry size variation, resulting as either under or over-allocate initial capital stocks across firms. To deal with the issue, the VML team then initialise the estimated total investment using a number for total investment in the year is established taken from the National Accounts for the industry j. The estimated total investment is then compared with observed investment in the ARDx to get a measure (ratio) of how much of the actual investment is observed in the ARDx. Multiplying the ratio with the estimated total capital stocks provides the total observed capital stocks for the industry. The initial total observed capital stock is then allocated to each firm using IDBR report unit's turnover as the weight. PIM is then employed to carry forward the capital stock variable.

[4] Interpreting a "reporting unit" as a firm is consistent with an ONS paper by Black (2022) and with recent studies such as Gobey and Matikonis (2021) and, more recently, Hall and Manning (2024), among others. According to ONS business activity documentation (ONS, 2017), a "reporting unit" may comprise a collection of plants, referred to as "local units" and identified as "luref" in the data.

[5] Industry (division) level deflators from Q1 (Jan-Mar) 1997 to Q2 (Apr-Jun) 2024 at annual, quarterly and monthly frequency. Data can be accessed here: https://www.ons.gov.uk/file?uri=/economy/grossdomesticproductgdp/datasets/industrydeflators/current/previous/v3/industrydeflatorsq22024.xlsx

[6] Producer Price Indices can be accessed here: https://www.ons.gov.uk/economy/inflationandpriceindices/datasets/producerpriceindex

Table 1 presents the summary statistics in natural logarithms, showing firm-level averages for key variables: revenue, number of employees, material expenditure, total capital stock, capital investment in land and buildings, software and databases, other capital stock, and aggregate industry revenue.

Table 2 reveals distinct patterns of capital intensity across manufacturing sectors. Column (1), which refers to the total capital stock variable, indicates that sectors such as SIC19 (Coke and refined petroleum products), SIC10 (Food products), and SIC29 (Motor vehicles) are relatively more capital-intensive. As shown in column (2), Food products (SIC10), Coke and refined petroleum products (SIC19), and again Motor vehicles (SIC29) consistently appear as the most tangible capital-intensive sectors. However, sectors including Food products (SIC10), Beverages (SIC11), Coke and refined petroleum products (SIC19), Basic pharmaceutical products and pharmaceutical preparations (SIC21), Motor vehicles (SIC29), and other transport equipment (SIC30) exhibit greater intangible capital intensity than the rest of the manufacturing sector. [7]

4 Results

4.1 Revenue Elasticities, Implied Output Elasticities, and Returns to Scale

Table 3a presents the results from the baseline structural model assuming homogeneous capital investment across firms, estimating the revenue function for SIC 2-digit sectors within manufacturing. Table 3b summarises the implied output elasticities.

While the unweighted average of the returns to scale parameters is approximately 0.874 – not too far from constant returns – we observe several industries with decreasing returns to scale, in some cases falling below 0.6 or even 0.5. For example, returns to scale are identified as below 0.5 for Leather and Related Products (SIC 15) and Computer, Electronic and Optical Products (SIC 26), and below 0.6 for Machinery and Equipment n.e.c. (SIC 28) and Repair and Installation of Machinery and Equipment (SIC 33).

Table 4a presents the results from the structural model allowing for heterogeneous capital investment across firms. Table 4b again summarises the implied output elasticities. As before, column (1) of Table 4a reports the coefficient on the deflated industry revenue variable, while columns (2) to (6) report the estimated

[7] This is consistent with the findings of van Ark, de Vries, and Erumban (2023), who report that the growth of intangible capital services in sectors such as Food Services (as well as Transportation, and Accommodation) has accelerated since the GFC.

revenue elasticities with respect to each input. Given that this estimation framework distinguishes between three types of capital investment, we present the revenue elasticities for capital in land and buildings (column 3), software and databases (column 4), and other capital goods (column 5).

An immediate observation is that capital heterogeneity significantly affects the estimated revenue elasticities. For example (in Table 3a) firms in the Food Products sector (SIC 10) appear to have a high output elasticity with respect to capital when capital is treated homogeneously (with sector average estimated coefficient 0.303); however, Table 4a reveals that this elasticity is driven by intangible capital (software and databases, with sector average estimated coefficient 0.048), rather than by tangible capital such as land and buildings. Similar patterns are observed across other industries.

In Table 4b, columns (1) to (5) report the implied output elasticities with respect to each type. Overall, we find that the unweighted average of the returns to scale parameters increases slightly when capital heterogeneity is accounted for. This adjustment is particularly notable in several sectors: Leather and Related Products (SIC 15), where the returns to scale increase from 0.472 to 1.169; Computer, Electronic and Optical Products (SIC 26), from 0.474 to 0.634; Machinery and Equipment n.e.c. (SIC 28), from 0.560 to 0.665; and Repair and Installation of Machinery and Equipment (SIC 33), from 0.579 to 0.647.

Tables 5a and 5b incorporate adjustment costs in labour and capital across firms. The results indicate that adjustment costs also influence the estimated revenue elasticities. To facilitate a more detailed comparison, Table 6 summarises the returns to scale across the three model specifications. Overall, the results display considerable variation.

To provide further insight into adjustment costs, we plot the estimated fixed and variable adjustment costs for labour (Figure 3) and capital (Figures 4 to 6). Overall, the fixed component of labour adjustment costs appears relatively similar across most sectors, with the exception of Leather and related products (SIC15), Coke and refined petroleum products (SIC19), Non-metallic mineral products (SIC23), Fabricated metal products (SIC25), Machinery and equipment (SIC28), Motor vehicles (SIC29), Furniture (SIC31), and Other manufacturing (SIC32).

In contrast, the fixed component of capital adjustment costs associated with intangible capital varies substantially over sectors and over time (Figure 5), especially in sectors such as Textiles (SIC13), Wearing apparel (SIC14), Leather and related products (SIC15), Wood products (SIC16), Rubber and plastic products (SIC22), Non-metallic mineral products (SIC23), Basic metals (SIC24), Fabricated metal products (SIC25), Furniture (SIC31), and Other manufacturing (SIC32). We also observe notable variation in the fixed component of tangible capital investment across sectors and over time (Figure 4).

4.2 Evolution of the level of TFP

Figure 7 plots the distribution across the three TFP measures – $TFPQ^{*}$ (black dash line), $TFPQ^{*K}$ (gray dash line), and $TFPQ^{*KV}$ (red line). The TFP measure derived using the extended framework – which accounts for heterogeneous capital and firms' adjustment costs – is notably higher than the baseline measure $TFPQ^{*}$. Figure 8 presents the evolution of these TFP measures, each aggregated to the industry level using firm revenue weights. We find that the specification incorporating heterogeneous capital and adjustment costs (blue line) consistently yields the highest TFP estimate throughout the period 1997–2020.

Furthermore, when comparing to the evolution of capital investment across three different types of capital, the results suggest that TFP dynamics are shaped by shifts in both tangible and intangible capital. For instance, Panel A of Figure 9 shows that firms' investment in tangible capital declined by approximately 7 percentage points between 1997 and 2001, about 6-7 percentage points between 2002 and 2011, and by more than 10 percentage points in total between 1997-2020. The $TFPQ^{*KV}$ measure appears to capture this declining trend; it shows an overall decline of roughly 9-10 percentage points over the period (the blue line in Figure 8). However, when focusing on the baseline $TFPQ^{*}$ (the black dashed line in Figure 8) it suggests a larger decline, exceeding 15 percentage points over the same timeframe.

In Panel B of Figure 9, we find an overall upward trend in intangible capital investment; from 2001 to the end of 2020, manufacturing firms increased their investment in capital such as software and databases by more than 2 percentage points. We find that the extended measure (taking into account both capital heterogeneity and firms' adjustment costs) reflects the rise in intangible investment, particularly during the post GFC period; though the $TFPQ^{*KV}$ declines between 2009 and 2010, in 2011 it shows a slight increase, followed by another rise in 2015 and 2018.

4.3 TFP Growth

We adopt the De Loecker et al. (2020) decomposition, subsequently used in Coyle at el. (2024) and Coyle, Bournakis, and Mei (2025), representing the growth rate of the aggregate TFP as sum of a number of components:

$$\Delta x_t = \sum_i \Delta x_{it} S_{it-1} + \sum_i \hat{x}_{it-1} \Delta S_{it} + \sum_i \Delta x_{it} \Delta S_{it} + \sum_{i \in Entry} \hat{x}_{it} S_{it} + \sum_{i \in Exit} \hat{x}_{it-1} S_{it-1}. \quad (18)$$

where Δx_t represents the growth rate of the TFP measure (log differenced), $\hat{x}_{it} = x_{it} - x_{t-1}$ $\hat{x}_{it-1} = x_{it-1} - x_{t-1}$, and $x_t = \sum_i x_{it} S_{it}$. The first term on the right-hand side of equation (18) is the effect of within-firm productivity growth on the sector aggregate growth rate. The combination of the two terms $\sum_i \hat{x}_{it-1} \Delta S_{it}$ and $\sum_i \Delta x_{it} \Delta S_{it}$ captures reallocation effects between firms in the sector. The combination of the final two terms $\sum_{i \in Entry} \hat{x}_{it} S_{it}$ and $\sum_{i \in Exit} \hat{x}_{it-1} S_{it-1}$ then captures the effects of firms' net entry. For clarity, we combine the reallocation and net-entry terms into a single broad reallocation term. We set the level of the index equal to 1 in 2009 and use relevant calculated weighted growth rates to infer its evolution over time.

Figure 10 presents the growth of revenue-share weighted TFP, decomposed into overall growth (Panel A), within-firm growth (Panel B), and reallocation (Panel C). We report results using three alternative measures: $TFPQ^{*}$ (black line), $TFPQ^{*K}$ (grey line), and $TFPQ^{*KV}$ (red line). The trends are further disaggregated into two sub-periods: 1997-2008 (pre-GFC) and 2010-2020 (post-GFC).

First, the growth of $TFPQ^{*}$ shows a modest decline in its growth between the pre- and post-GFC periods. Second, both the $TFPQ^{*K}$ and $TFPQ^{*KV}$ indices exhibit a relatively stable pattern across the period – suggesting that, overall, the productivity slowdown in manufacturing has been relatively mild (albeit still present), rather than steep. Notably, the average growth across the two periods is higher for both $TFPQ^{*K}$ and $TFPQ^{*KV}$ than for $TFPQ^{*}$.

Third, when we decompose the overall index into the within-firm effect (Panel B) and a broad reallocation effect (Panel C) we find there is a fall in the within-firm growth measure of $TFPQ^{*}$ between 2010 and 2020 by roughly 10% (from above 1.1 in 2010 to below 1 in 2020). This is consistent with the striking finding in Coyle at el. (2024) of a within-firm growth TFP decline of 13% during 2008-2019. However, while the extended measure $TFPQ^{*KV}$ shows that there is a decline, it is milder; for the period 2010-2020, about 5%. When comparing with both pre- and post-GFC trends, we find that both $TFPQ^{*K}$ and $TFPQ^{*KV}$ show moderate slowdowns, in contrast to $TFPQ^{*}$'s sharp slowdown. Panel C shows that all three measures show positive trends in the reallocation term across the two periods. However, the reallocation term identified by the $TFPQ^{*}$ measure is generally smaller than the others.

5 Conclusion

This paper studies the role of capital heterogeneity and adjustment costs across firms in the estimation of TFP, using UK manufacturing firm-level data covering the period 1997–2020. We build upon an existing structural framework based on the firm-level revenue function, extending it by relaxing the assumption of homogeneous capital and incorporating adjustment costs. We then compare the alternative TFP measures with a baseline standard approach.

Our first main result shows that capital heterogeneity and adjustment costs significantly influence the estimation of revenue elasticities, leading to an underestimate of firms' TFP when these factors are omitted. Specifically, the unweighted average of the returns-to-scale parameters increases modestly once capital heterogeneity and adjustment costs are incorporated. Notably, we find that the component associated with intangible capital varies substantially across sectors and over time.

Secondly, we find that the TFP measure derived using our extended framework – which accounts for heterogeneous capital and adjustment costs – is markedly higher than the conventional TFP measure. In particular, our results suggest that the $TFPQ^{*KV}$ measure (in level) effectively suggests an overall TFP decline of approximately 9-10 percentage points over the period 1997-2020. By contrast, the standard measure commonly used in the literature – $TFPQ^{*}$ – implies a decline exceeding 15 percentage points over the same timeframe.

Thirdly, the data indicate a general upward trend in intangible capital investment over time. We find that the extended measure, which accounts for both capital heterogeneity and firms' adjustment costs ($TFPQ^{*KV}$), closely reflects this rise in intangible investment, particularly during the post-GFC period.

Finally, in contrast to the notable decline in its overall TFPQ* growth trajectory between the pre- and post-GFC periods, as found in prior estimates, both the alternative

$TFPQ^{*K}$ and $TFPQ^{*KV}$ indices display a more moderate slowdown. When we decompose the overall TFP index into the within-firm effect and a broad reallocation effect, the results reveal a mild decline of around 5% in the extended measures, compared with a decline of approximately 10% in the within-firm component of the standard $TFPQ^{*}$ between 2010 and 2020.

Our results therefore suggest that capital heterogeneity significantly influences the estimation of revenue elasticities, and that adjustment costs in both labour and capital also vary substantially across firms. These variations lead to notable differences in the evolution of estimated TFP. We find that the TFP measure which incorporates heterogeneous capital and adjustment costs consistently yields higher productivity estimates across the period 1997-2020. More importantly, our findings indicate that the productivity slowdown within manufacturing is mild rather than severe when these factors are appropriately accounted for within the estimation framework.

Our findings speak to the extensive discussion in the UK productivity puzzle. If TFP growth in manufacturing is more stable than previously thought, then the pronounced slowdown in labour productivity must originate elsewhere. A plausible candidate is the investment channel; since the mid-2000s, UK manufacturing has experienced weak capital deepening and declining investment in machinery and equipment, particularly in technology, digital intensive (Goodridge and Haskel, 2023) and capital-goods-producing industries (Alayande and Coyle, 2023; Patton, 2025). Chadha and Samiri (2026) also highlight that the UK's private and public investment have trended downward since the mid-2000s, contributing to capital shallowing and weak TFP growth. The rise of intangible-intensive production – which entails high adjustment costs and is only partially captured in standard measures – further strengthen this pattern. The fact that our TFP measures remain comparatively resilient is therefore consistent with an interpretation in which low investment, rather than a collapse in underlying technological progress, drove aggregate manufacturing performance.

The perspective that emerges from our analysis is thus less pessimistic than the conventional narrative. The shift toward intangible capital, combined with adjustment costs for both tangible and intangible assets, alters the estimation and interpretation of TFP measures in ways that reduce the apparent severity of the post-GFC slowdown. Nevertheless, a more detailed exploration of the interaction between capital heterogeneity, investment behaviour, and adjustment frictions is needed, particularly in light of ongoing technological change.

All Tables and Graphs

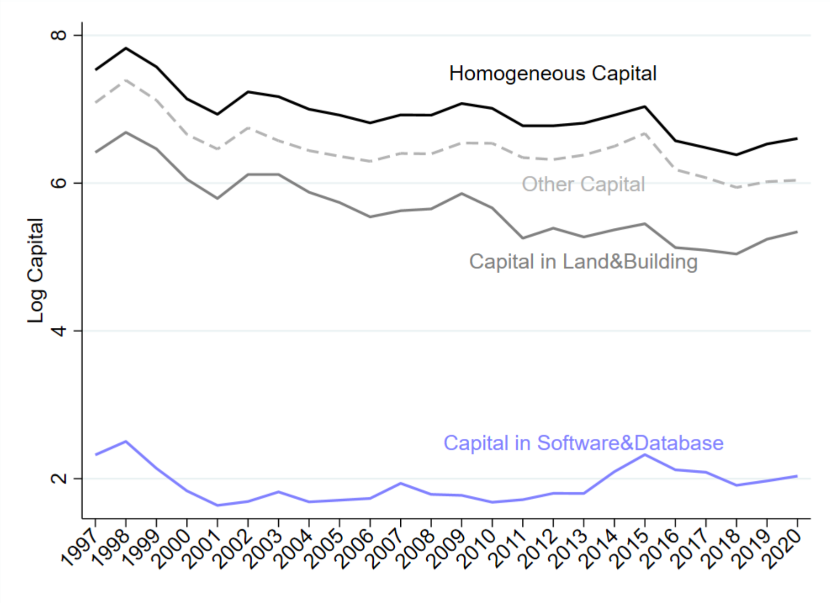


Figure 1. Capital Heterogeneity 1997-2020 - Manufacturing

Notes: Capital stocks are aggregated in logarithms and weighted by firms' revenue shares within the manufacturing industry. The figure shows that manufacturing follows a distinct capital trajectory, with more pronounced declines in traditional tangible assets and comparatively slower growth in high-value intangible assets. Although intangible capital begins from a much lower base, the series for software and databases exhibits a modest but noticeable increase from the early 2010s onwards. Because this category is plotted on the same log scale as much larger tangible stocks, its growth appears visually muted; nevertheless, the figure indicates that intangible investment has remained stable or risen slightly while tangible capital has steadily declined through the 2010s.

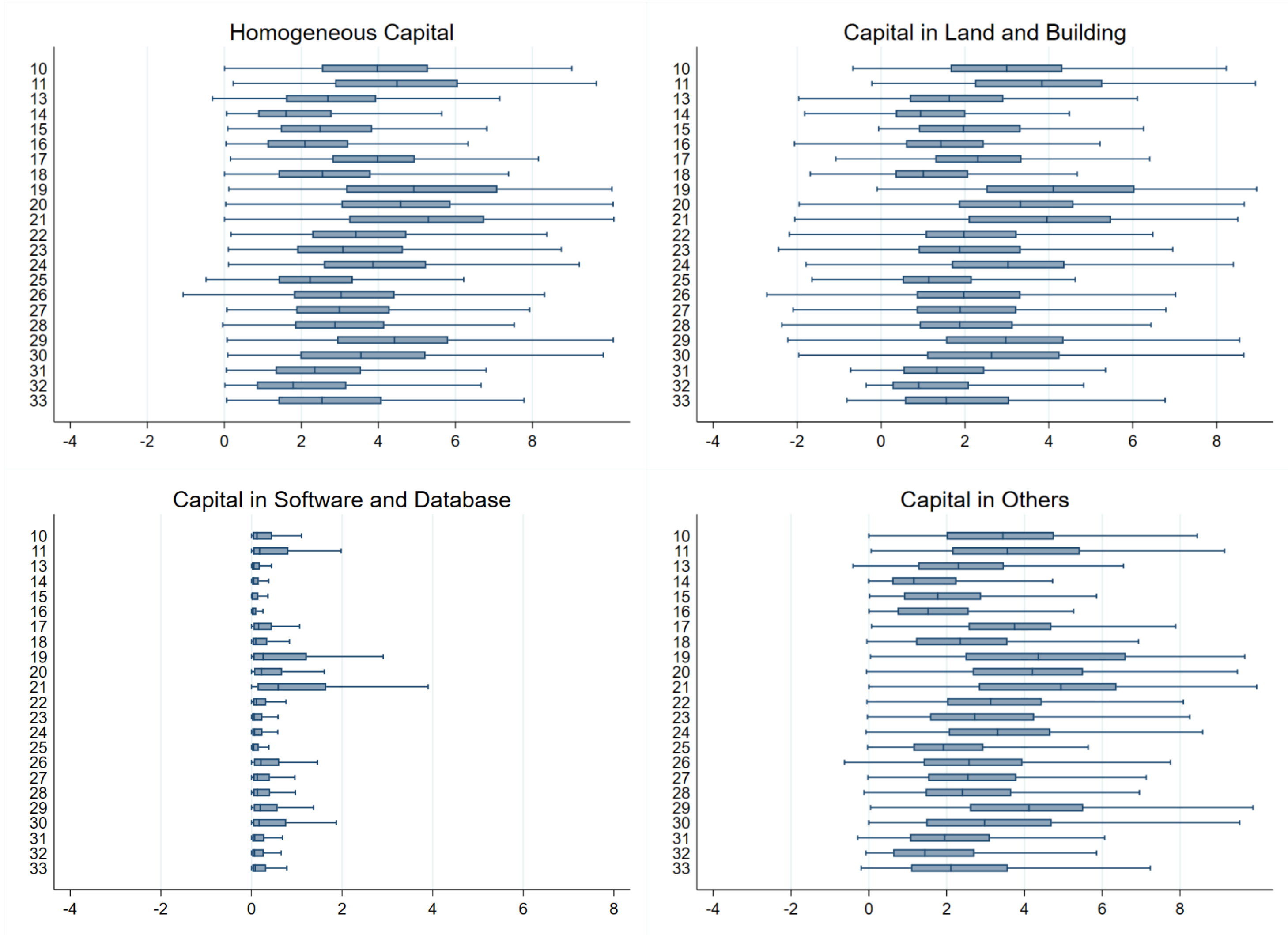


Figure 2. Distribution of Capital Assets Across Firms Within Manufacturing Industries

Notes: Each panel shows the distribution (log scale) of firm-level capital stocks within manufacturing industries for four asset categories: homogeneous capital, land and buildings, software and databases, and other capital. The horizontal bars represent the dispersion of capital holdings across firms within each industry. There are 208,661 firm-year observations in total.

Table 1. Summary Statistics

	Mean	Std.	Min	Max	Obs
Revenue	3.306	1.800	0	12.547	208,661
Employees	3.933	1.640	0	10.556	208,661
Materials	3.418	2.080	0	11.975	208,661
Capital	3.210	1.842	-1.070	11.176	208,661
Capital b	2.216	1.677	-5.375	10.627	208,661
Capital s	0.334	0.601	0	8.827	208,661
Capital o	2.833	1.778	-2.203	10.983	208,661
Industry Revenue	10.945	0.854	4.021	13.894	208,661

Notes: All variables are in logarithm. Capital b refers to capital stock in land and building, Capital s refers to capital stock in software and database, and Capital o refers to other capital stock.

Table 2. Capital Investment Intensity, Relative to the whole Manufacturing Industry

	All Capital Goods (1)	Land & Building (2)	Software & Database (3)	Others (4)
Sic10	0.122	0.125	0.100	0.122
Sic11	0.066	0.072	0.070	0.065
Sic13	0.006	0.005	0.003	0.006
Sic14	0.003	0.003	0.002	0.003
Sic15	0.001	0.001	0.001	0.001
Sic16	0.006	0.006	0.002	0.006
Sic17	0.017	0.015	0.010	0.017
Sic18	0.010	0.008	0.007	0.010
Sic19	0.241	0.257	0.276	0.238
Sic20	0.074	0.072	0.057	0.076
Sic21	0.063	0.060	0.105	0.065
Sic22	0.026	0.022	0.013	0.027
Sic23	0.029	0.028	0.018	0.029
Sic24	0.031	0.033	0.013	0.030
Sic25	0.030	0.026	0.017	0.029
Sic26	0.028	0.026	0.029	0.028
Sic27	0.015	0.013	0.010	0.015
Sic28	0.042	0.040	0.038	0.041
Sic29	0.090	0.085	0.110	0.093
Sic30	0.062	0.066	0.083	0.062
Sic31	0.007	0.006	0.005	0.007
Sic32	0.011	0.010	0.012	0.011
Sic33	0.020	0.020	0.016	0.020

Notes: Columns may not sum to 1 due to rounding. All numbers are revenue shares weighted. Numbers refer to capital intensity related to the whole manufacturing. For instance, in the universe capital stock variable column 1, sectors such as SIC19, SIC10, and SIC29 are found to be capital intensive compared to other sectors. When distinguishing capital into land and building, as presented in column (2), sectors such as SIC10, SIC19, and again SIC29 are found to be land and building intensive than others. When distinguishing capital into software and database, it shows that sectors such as SIC10, SIC11, SIC19, SIC21, SIC29, and SIC30 are more capital intensive in "intangible" capital than others. There are 208,661 observations.

Table 3a. Estimation of Revenue Function for 2-Digit Manufacturing Industries with Homogeneous Capital Assumption – Revenue Elasticities

	$1/\eta_j$ (1)	$((\eta_j-1)/\eta_j)\beta_j^l$ (2)	$((\eta_j-1)/\eta_j)\beta_j^k$ (3)	$((\eta_j-1)/\eta_j)\beta_j^m$ (4)
SIC10	0.022**	0.168***	0.303***	0.037***
(Food Products)	(0.011)	(0.032)	(0.036)	(0.015)
SIC11	0.005	0.142**	0.303***	0.255***
(Beverages)	(0.011)	(0.068)	(0.075)	(0.033)
SIC13	-0.056***	0.173***	0.230***	0.350***
(Textiles)	(0.014)	(0.071)	(0.070)	(0.029)
SIC14	-0.007	0.380***	0.378***	0.240***
(Wearing apparel)	(0.015)	(0.075)	(0.091)	(0.044)
SIC15	-0.102***	0.300*	0.215	0.006
(Leather and related products)	(0.026)	(0.163)	(0.156)	(0.073)
SIC16	0.025*	0.614***	0.421***	0.140***
(Wood Products)	(0.014)	(0.086)	(0.085)	(0.034)
SIC17	-0.060***	0.476***	0.513***	0.133***
(Paper Products)	(0.016)	(0.063)	(0.068)	(0.025)
SIC18	-0.029***	0.326***	0.119***	0.246***
(Printing & Reproduction)	(0.012)	(0.058)	(0.051)	(0.030)
SIC19	0.020	0.456***	0.579***	0.357***
(Coke and refined)	(0.021)	(0.180)	(0.103)	(0.083)
SIC20	-0.003	0.287***	0.419***	0.213***
(Chemicals)	(0.012)	(0.055)	(0.066)	(0.028)
SIC21	0.030	0.578***	0.287***	0.369***
(Basic pharmaceutical products and pharmaceutical preparations)	(0.019)	(0.087)	(0.110)	(0.048)
SIC22	0.049***	0.479***	0.319***	0.237***
(Rubber & Plastic)	(0.016)	(0.061)	(0.065)	(0.026)
SIC23	0.019	0.456***	0.406***	0.320***
(Non-Metallic Mineral)	(0.013)	(0.054)	(0.059)	(0.021)
SIC24	0.013	0.121*	0.256***	0.311***
(Basic Metals)	(0.012)	(0.065)	(0.097)	(0.028)
SIC25	-0.049***	0.444***	0.186***	0.100***
(Fabricated Metal)	(0.013)	(0.055)	(0.055)	(0.024)
SIC26	0.010	0.147***	0.159***	0.163***
(Comp., Elec. & Optical)	(0.016)	(0.059)	(0.041)	(0.030)
SIC27	-0.021	0.600***	0.281***	0.128***
(Electrical Equipment)	(0.015)	(0.073)	(0.080)	(0.031)
SIC28	0.064***	0.07	0.230***	0.222***
(Machinery and Eqp. n.e.c.)	(0.013)	(0.057)	(0.052)	(0.019)
SIC29	0.004	0.578***	0.555***	0.138***
(Motor Vehicles)	(0.013)	(0.072)	(0.085)	(0.033)
SIC30	0.129	0.350***	0.305***	0.375***
(Other Transport Eqp.)	(0.016)	(0.064)	(0.085)	(0.032)
SIC31	-0.029*	0.344***	0.351***	0.276***
(Furniture)	(0.015)	(0.076)	(0.077)	(0.030)
SIC32	-0.090***	0.593***	0.136***	0.061**
(Other Manufacturing)	(0.016)	(0.084)	(0.045)	(0.028)
SIC33	-0.005	0.355***	0.109	0.118***
(Repair and Installation)	(0.014)	(0.069)	(0.076)	(0.037)

Notes: Column (1) reports the coefficient on the deflated industry revenue variable, where the inverse of this coefficient provides an estimate of the demand-side elasticity of substitution in the industry. Columns (2) to (4) report the estimated revenue elasticities with respect to each input. The mean average elasticity of labour is 0.33, the mean average elasticity of capital is 0.27, and the mean average elasticity of material is 0.08. Robust standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively.

Table 3b. Estimation of Revenue Function for 2-Digit Manufacturing Industries with Homogeneous Capital Assumption – Implied Output Elasticities

	β_j^l (1)	β_j^k (2)	β_j^m (3)	$\bar{\beta}_j$ (4)
SIC10 (Food Products)	0.172	0.310	0.039	0.521
SIC11 (Beverages)	0.143	0.304	0.256	0.703
SIC13 (Textiles)	0.163	0.218	0.332	0.713
SIC14 (Wearing apparel)	0.378	0.376	0.238	0.992
SIC15 (Leather and related products)	0.272	0.195	0.005	0.472
SIC16 (Wood Products)	0.629	0.431	0.052	1.112
SIC17 (Paper Products)	0.450	0.484	0.125	1.059
SIC18 (Printing & Reproduction)	0.317	0.116	0.238	0.671
SIC19 (Coke and refined)	0.465	0.591	0.364	1.420
SIC20 (Chemicals)	0.286	0.418	0.212	0.916
SIC21 (Basic pharmaceutical products and pharmaceutical preparations)	0.596	0.296	0.380	1.272
SIC22 (Rubber & Plastic)	0.505	0.335	0.249	1.089
SIC23 (Non-Metallic Mineral)	0.465	0.414	0.326	1.205
SIC24 (Basic Metals)	0.109	0.259	0.315	0.683
SIC25 (Fabricated Metal)	0.423	0.178	0.095	0.696
SIC26 (Comp., Elec. & Optical)	0.149	0.161	0.164	0.474
SIC27 (Electrical Equipment)	0.588	0.275	0.125	0.988
SIC28 (Machinery and Eqp. n.e.c.)	0.075	0.247	0.238	0.560
SIC29 (Motor Vehicles)	0.580	0.557	0.139	1.276
SIC30 (Other Transport Eqp.)	0.355	0.309	0.380	1.044
SIC31 (Furniture)	0.334	0.341	0.268	0.943
SIC32 (Other Manufacturing)	0.543	0.125	0.056	0.724
SIC33 (Repair and Installation)	0.353	0.108	0.118	0.579

Notes: $\bar{\beta}_j = \beta_j^l + \beta_j^k + \beta_j^m$. Columns (1) to (3) present the implied output elasticities corresponding to these inputs, inferred based on the elasticity of substitution estimated in Table 3a. Column (4) shows the implied estimate of returns to scale.

Table 4a. Estimation of Revenue Function for 2-Digit Manufacturing Industries without the Fraction of Capital Investment Accounted for – Revenue Elasticities

	$1/\eta_j$	$((\eta_j-1)/\eta_j)\beta_j^l$	$((\eta_j-1)/\eta_j)\beta_j^{kb}$	$((\eta_j-1)/\eta_j)\beta_j^{ks}$	$((\eta_j-1)/\eta_j)\beta_j^{ko}$	$((\eta_j-1)/\eta_j)\beta_j^{m}$
	(1)	(2)	(3)	(4)	(5)	(6)
SIC10	0.012	0.168***	0.011	0.048***	0.026***	0.046**
(Food Products)	(0.010)	(0.031)	(0.022)	(0.017)	(0.036)	(0.015)
SIC11	0.003	0.154***	-0.003	0.028	0.279***	0.252***
(Beverages)	(0.009)	(0.064)	(0.022)	(0.025)	(0.072)	(0.031)
SIC13	-0.060***	0.206***	0.034	0.102**	0.171**	0.326***
(Textiles)	(0.013)	(0.068)	(0.027)	(0.050)	(0.079)	(0.029)
SIC14	-0.020	0.415***	0.102***	0.175***	0.128**	0.212***
(Wearing apparel)	(0.013)	(0.067)	(0.042)	(0.058)	(0.060)	(0.041)
SIC15	-0.054**	0.317**	-0.021	0.271***	0.643***	0.128*
(Leather and related products)	(0.026)	(0.165)	(0.112)	(0.112)	(0.159)	(0.075)
SIC16	0.038***	0.567***	0.016	0.131***	0.287***	0.159***
(Wood Products)	(0.012)	(0.080)	(0.030)	(0.051)	(0.083)	(0.032)
SIC17	-0.053	0.470***	0.059***	0.030	0.445***	0.125***
(Paper Products)	(0.013)	(0.061)	(0.023)	(0.037)	(0.073)	(0.025)
SIC18	-0.034***	0.275***	0.017	0.038	0.139***	0.235***
(Printing & Reproduction)	(0.010)	(0.055)	(0.020)	(0.030)	(0.055)	(0.029)
SIC19	0.039***	0.253	-0.013	0.116	0.748***	0.430***
(Coke and refined)	(0.018)	(0.166)	(0.086)	(0.093)	(0.132)	(0.085)
SIC20	-0.010	0.309***	0.004	0.033	0.420***	0.193***
(Chemicals)	(0.009)	(0.054)	(0.019)	(0.026)	(0.074)	(0.027)
SIC21	0.014	0.601***	0.094*	0.028	0.322***	0.338***
(Basic pharmaceutical products and pharmaceutical preparations)	(0.017)	(0.087)	(0.051)	(0.031)	(0.093)	(0.046)
SIC22	0.015	0.461***	0.001	0.044	0.313***	0.276***
(Rubber & Plastic)	(0.013)	(0.057)	(0.016)	(0.030)	(0.071)	(0.024)
SIC23	-0.002	0.484***	0.038*	0.121***	0.334***	0.344***
(Non-Metallic Mineral)	(0.011)	(0.052)	(0.022)	(0.028)	(0.060)	(0.020)
SIC24	0.027***	0.117**	-0.089*	0.020	0.352***	0.324***
(Basic Metals)	(0.009)	(0.059)	(0.042)	(0.041)	(0.085)	(0.027)
SIC25	-0.015	0.493***	0.016	0.026	0.254***	0.105***
(Fabricated Metal)	(0.011)	(0.052)	(0.021)	(0.033)	(0.056)	(0.022)
SIC26	0.044***	0.148***	0.035	0.120***	0.112***	0.184***
(Comp., Elec. & Optical)	(0.015)	(0.059)	(0.025)	(0.026)	(0.046)	(0.028)
SIC27	-0.016	0.593***	0.040	0.035	0.174***	0.119***
(Electrical Equipment)	(0.013)	(0.070)	(0.026)	(0.041)	(0.073)	(0.029)
SIC28	0.065***	0.128***	0.020	-0.0002	0.256***	0.216***
(Machinery and Eqp. n.e.c.)	(0.011)	(0.054)	(0.020)	(0.027)	(0.059)	(0.019)
SIC29	0.004	0.522***	0.022	0.100***	0.380***	0.113***
(Motor Vehicles)	(0.011)	(0.068)	(0.020)	(0.027)	(0.084)	(0.032)
SIC30	-0.001	0.337***	0.036	0.0002	0.199***	0.365***
(Other Transport Eqp.)	(0.013)	(0.062)	(0.027)	(0.029)	(0.089)	(0.031)
SIC31	-0.019	0.338***	-0.030	0.097***	0.397***	0.275***
(Furniture)	(0.013)	(0.072)	(0.032)	(0.037)	(0.085)	(0.030)
SIC32	-0.051	0.480***	-0.023	0.034	0.301***	0.046
(Other Manufacturing)	(0.015)	(0.080)	(0.024)	(0.034)	(0.073)	(0.030)
SIC33	-0.008	0.363***	-0.030	0.023	0.192**	0.127***
(Repair and Installation)	(0.012)	(0.068)	(0.033)	(0.043)	(0.088)	(0.035)

Notes: Robust standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively. The mean average elasticity of labour is 0.33, the mean average elasticity of capital in land and building is 0.01, the mean average elasticity of capital in software and database is 0.05, the mean average elasticity of capital in others is 0.27, and the mean average elasticity of material is 0.09.

Table 4b. Estimation of Revenue Function for 2-Digit Manufacturing Industries without the Fraction of Capital Investment Accounted for – Implied Output Elasticities

	β_j^l (1)	β_j^{kb} (2)	β_j^{ks} (3)	β_j^{ko} (4)	β_j^m (5)	$\bar{\beta}_j$ (6)
SIC10 (Food Products)	0.170	0.011	0.049	0.265	0.050	0.545
SIC11 (Beverages)	0.154	-0.003	0.028	0.281	0.253	0.713
SIC13 (Textiles)	0.190	0.032	0.096	0.161	0.307	0.786
SIC14 (Wearing apparel)	0.406	0.100	0.171	0.125	0.032	0.834
SIC15 (Leather and related products)	0.198	-0.020	0.257	0.610	0.124	1.169
SIC16 (Wood Products)	0.590	0.017	0.136	0.300	0.032	1.075
SIC17 (Paper Products)	0.445	0.056	0.030	0.422	0.120	1.073
SIC18 (Printing & Reproduction)	0.266	0.017	0.037	0.134	0.230	0.684
SIC19 (Coke and refined)	0.263	-0.002	0.067	0.778	0.459	1.565
SIC20 (Chemicals)	0.306	0.004	0.032	0.416	0.192	0.950
SIC21 (Basic pharmaceutical products and pharmaceutical preparations)	0.610	0.095	0.029	0.330	0.344	1.408
SIC22 (Rubber & Plastic)	0.468	0.001	0.044	0.320	0.280	1.113
SIC23 (Non-Metallic Mineral)	0.484	0.039	0.121	0.333	0.344	1.321
SIC24 (Basic Metals)	0.120	-0.092	0.020	0.362	0.333	0.743
SIC25 (Fabricated Metal)	0.486	0.015	0.030	0.300	0.001	0.832
SIC26 (Comp., Elec. & Optical)	0.155	0.037	0.125	0.118	0.199	0.634
SIC27 (Electrical Equipment)	0.584	0.040	0.035	0.172	0.118	0.949
SIC28 (Machinery and Eqp. n.e.c.)	0.138	0.022	-0.001	0.274	0.232	0.665
SIC29 (Motor Vehicles)	0.524	0.022	0.100	0.382	0.114	1.142
SIC30 (Other Transport Eqp.)	0.337	0.035	0.001	0.200	0.365	0.938
SIC31 (Furniture)	0.332	-0.029	0.100	0.390	0.270	1.063
SIC32 (Other Manufacturing)	0.458	-0.022	0.032	0.287	0.011	0.766
SIC33 (Repair and Installation)	0.360	-0.030	0.001	0.190	0.126	0.647

Notes: $\bar{\beta}_j = \beta_j^l + \beta_j^k + \beta_j^m$.

Table 5a. Estimation of Revenue Function for 2-Digit Manufacturing Industries with the Fraction of Capital Investment and Fixed-variable Costs – Revenue Elasticities

	$1/\eta_j$	$((\eta_j-1)/\eta_j)\beta_j^l$	$((\eta_j-1)/\eta_j)\beta_j^{kb}$	$((\eta_j-1)/\eta_j)\beta_j^{ks}$	$((\eta_j-1)/\eta_j)\beta_j^{ko}$	$((\eta_j-1)/\eta_j)\beta_j^{m}$
	(1)	(2)	(3)	(4)	(5)	(6)
SIC10	0.001***	0.200***	0.024	0.055***	0.194***	0.112***
(Food Products)	(0.008)	(0.031)	(0.021)	(0.017)	(0.032)	(0.020)
SIC11	0.005	0.125**	0.026	0.050**	0.011	0.241***
(Beverages)	(0.008)	(0.063)	(0.018)	(0.025)	(0.025)	(0.031)
SIC13	-0.055***	0.230***	0.050**	0.094*	0.189***	0.335***
(Textiles)	(0.012)	(0.066)	(0.025)	(0.053)	(0.054)	(0.028)
SIC14	0.004	0.404***	0.102***	0.195***	0.045	0.214***
(Wearing apparel)	(0.013)	(0.069)	(0.041)	(0.057)	(0.056)	(0.045)
SIC15	-0.010	0.192*	-0.004	0.239**	0.258***	0.101
(Leather and related products)	(0.025)	(0.116)	(0.084)	(0.113)	(0.082)	(0.076)
SIC16	0.050***	0.567***	0.020	0.145***	0.223***	0.154***
(Wood Products)	(0.011)	(0.080)	(0.028)	(0.051)	(0.059)	(0.031)
SIC17	-0.058***	0.396***	0.057***	0.053	0.010***	0.172***
(Paper Products)	(0.011)	(0.060)	(0.023)	(0.037)	(0.035)	(0.025)
SIC18	-0.028***	0.294***	0.035*	0.042	0.054*	0.246***
(Printing & Reproduction)	(0.008)	(0.055)	(0.019)	(0.030)	(0.031)	(0.029)
SIC19	0.016	0.170	0.105**	0.218***	0.291***	0.326***
(Coke and refined)	(0.017)	(0.146)	(0.050)	(0.087)	(0.050)	(0.084)
SIC20	-0.012	0.365***	-0.016	-0.016	0.288***	0.204***
(Chemicals)	(0.008)	(0.053)	(0.019)	(0.024)	(0.054)	(0.027)
SIC21	0.039**	0.335***	0.087**	0.032	0.044	0.335***
(Basic pharmaceutical products and pharmaceutical preparations)	(0.017)	(0.047)	(0.041)	(0.030)	(0.030)	(0.047)
SIC22	0.003	0.468***	-0.010	0.064**	0.030	0.301***
(Rubber & Plastic)	(0.010)	(0.055)	(0.015)	(0.029)	(0.040)	(0.024)
SIC23	-0.010	0.531***	0.044**	0.128***	0.213***	0.341***
(Non-Metallic Mineral)	(0.010)	(0.051)	(0.022)	(0.027)	(0.045)	(0.020)
SIC24	0.027***	0.138***	0.011	-0.015	0.244***	0.330***
(Basic Metals)	(0.009)	(0.058)	(0.037)	(0.039)	(0.046)	(0.027)
SIC25	-0.025***	0.507***	0.003	0.020	0.211***	0.124***
(Fabricated Metal)	(0.009)	(0.052)	(0.020)	(0.032)	(0.039)	(0.022)
SIC26	0.013	0.162***	0.050**	0.092***	0.077**	0.187***
(Comp., Elec. & Optical)	(0.012)	(0.060)	(0.025)	(0.026)	(0.038)	(0.029)
SIC27	-0.004	0.604***	0.028	0.017	0.266***	0.141***
(Electrical Equipment)	(0.011)	(0.069)	(0.025)	(0.041)	(0.047)	(0.029)
SIC28	0.064***	0.117**	0.011	0.005	0.259***	0.228***
(Machinery and Eqp. n.e.c.)	(0.011)	(0.053)	(0.019)	(0.027)	(0.049)	(0.018)
SIC29	0.020*	0.632***	0.030	0.110***	0.135***	0.130***
(Motor Vehicles)	(0.012)	(0.064)	(0.020)	(0.027)	(0.038)	(0.032)
SIC30	-0.004	0.343***	-0.052	0.025	0.113*	0.398***
(Other Transport Eqp.)	(0.012)	(0.062)	(0.028)	(0.029)	(0.060)	(0.030)
SIC31	0.012	0.397***	0.024	0.068*	0.046	0.290***
(Furniture)	(0.012)	(0.071)	(0.030)	(0.037)	(0.030)	(0.030)
SIC32	-0.054***	0.521***	-0.037	0.038	0.200***	0.041
(Other Manufacturing)	(0.013)	(0.078)	(0.024)	(0.034)	(0.063)	(0.031)
SIC33	-0.014	0.403***	-0.029	0.015	0.042	0.122***
(Repair and Installation)	(0.011)	(0.066)	(0.032)	(0.043)	(0.052)	(0.035)

Notes: $\bar{\beta}_j = \beta_j^l + \beta_j^k + \beta_j^m$. Robust standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively. The mean average elasticity of labour is 0.36, the mean average elasticity of capital in land and building is 0.02, the mean average elasticity of capital in software and database is 0.05, the mean average elasticity of capital in others is 0.16, and the mean average elasticity of material is 0.10.

Table 5b. Estimation of Revenue Function for 2-Digit Manufacturing Industries with the Fraction of Capital Investment Accounted For – Implied Output Elasticities

	β_j^l (1)	β_j^{kb} (2)	β_j^{ks} (3)	β_j^{ko} (4)	β_j^m (5)	$\bar{\beta}_j$ (6)
SIC10 (Food Products)	0.200	0.024	0.055	0.194	0.054	0.527
SIC11 (Beverages)	0.125	0.027	0.050	0.011	0.242	0.455
SIC13 (Textiles)	0.218	0.047	0.090	0.180	0.318	0.853
SIC14 (Wearing apparel)	0.407	0.102	0.196	0.046	0.034	0.785
SIC15 (Leather and related products)	0.190	-0.004	0.236	0.255	0.010	0.687
SIC16 (Wood Products)	0.596	0.021	0.152	0.234	0.040	1.043
SIC17 (Paper Products)	0.371	0.053	0.050	0.090	0.163	0.727
SIC18 (Printing & Reproduction)	0.286	0.034	0.040	0.052	0.239	0.651
SIC19 (Coke and refined)	0.172	0.107	0.221	0.295	0.331	1.126
SIC20 (Chemicals)	0.361	-0.016	-0.016	0.284	0.201	0.814
SIC21 (Basic pharmaceutical products and pharmaceutical preparations)	0.348	0.090	0.034	0.046	0.348	0.866
SIC22 (Rubber & Plastic)	0.470	-0.001	0.065	0.030	0.302	0.866
SIC23 (Non-Metallic Mineral)	0.528	0.044	0.127	0.212	0.340	1.251
SIC24 (Basic Metals)	0.142	0.011	-0.016	0.250	0.340	0.727
SIC25 (Fabricated Metal)	0.494	0.003	0.020	0.210	0.010	0.737
SIC26 (Comp., Elec. & Optical)	0.164	0.050	0.100	0.078	0.189	0.581
SIC27 (Electrical Equipment)	0.602	0.030	0.017	0.265	0.140	1.054
SIC28 (Machinery and Eqp. n.e.c.)	0.125	0.012	0.010	0.277	0.243	0.667
SIC29 (Motor Vehicles)	0.644	0.030	0.112	0.138	0.132	1.056
SIC30 (Other Transport Eqp.)	0.342	-0.053	0.026	0.030	0.400	0.745
SIC31 (Furniture)	0.403	0.025	0.070	0.014	0.294	0.806
SIC32 (Other Manufacturing)	0.495	-0.035	0.036	0.190	0.010	0.696
SIC33 (Repair and Installation)	0.397	-0.030	0.010	0.041	0.120	0.538

Notes: $\bar{\beta}_j = \beta_j^l + \beta_j^k + \beta_j^m$.

Table 6. Estimation of Revenue Function for 2-Digit Manufacturing Industries with the Fraction of Capital Investment Accounted For – Implied Output Elasticities

	$\bar{\beta}_j$ -Baseline (1)	$\bar{\beta}_j$ - K (2)	$\bar{\beta}_j$ - KV (3)
SIC10 (Food Products)	0.521	0.545	0.527
SIC11 (Beverages)	0.703	0.713	0.455
SIC13 (Textiles)	0.713	0.786	0.853
SIC14 (Wearing apparel)	0.992	0.834	0.785
SIC15 (Leather and related products)	0.472	1.169	0.687
SIC16 (Wood Products)	1.112	1.075	1.043
SIC17 (Paper Products)	1.059	1.073	0.727
SIC18 (Printing & Reproduction)	0.671	0.684	0.651
SIC19 (Coke and refined)	1.420	1.565	1.126
SIC20 (Chemicals)	0.916	0.950	0.814
SIC21 (Basic pharmaceutical products and pharmaceutical preparations)	1.272	1.408	0.866
SIC22 (Rubber & Plastic)	1.089	1.113	0.866
SIC23 (Non-Metallic Mineral)	1.205	1.321	1.251
SIC24 (Basic Metals)	0.683	0.743	0.727
SIC25 (Fabricated Metal)	0.696	0.832	0.737
SIC26 (Comp., Elec. & Optical)	0.474	0.634	0.581
SIC27 (Electrical Equipment)	0.988	0.949	1.054
SIC28 (Machinery and Eqp. n.e.c.)	0.560	0.665	0.667
SIC29 (Motor Vehicles)	1.276	1.142	1.056
SIC30 (Other Transport Eqp.)	1.044	0.938	0.745
SIC31 (Furniture)	0.943	1.063	0.806
SIC32 (Other Manufacturing)	0.724	0.766	0.696
SIC33 (Repair and Installation)	0.579	0.647	0.538

Notes: $\bar{\beta}_j = \beta_j^l + \beta_j^k + \beta_j^m$. Column (1) refers to the baseline, in which the model does not allow capital to be heterogeneous. Column (2) refers to the specification in which capital is treated as heterogeneous through land, building, database, software, and others. Column (3) allows for costs in labour and capital to be variable.

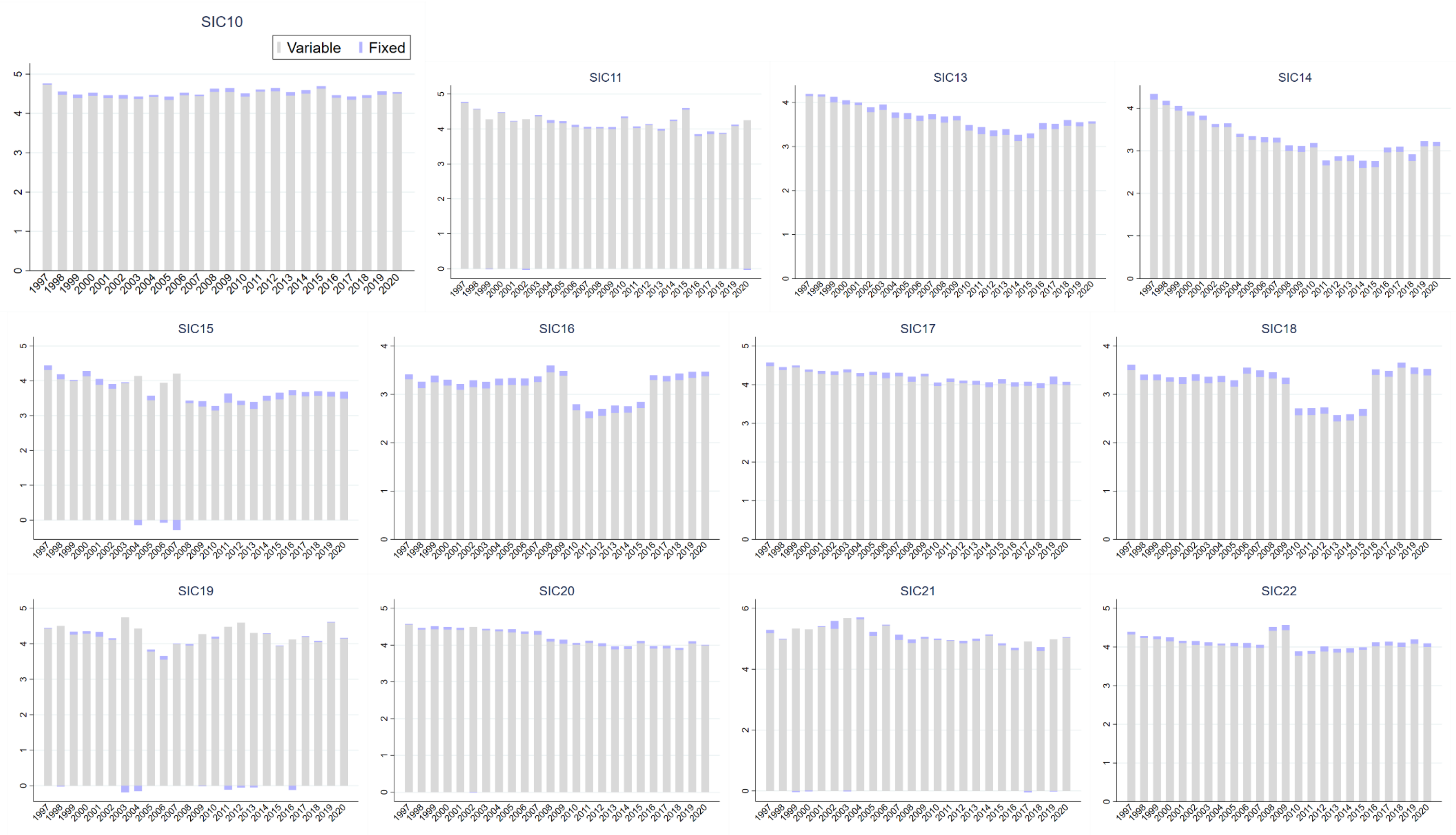


Figure 3. Fixed and Variable Costs in Labour Input (continued)

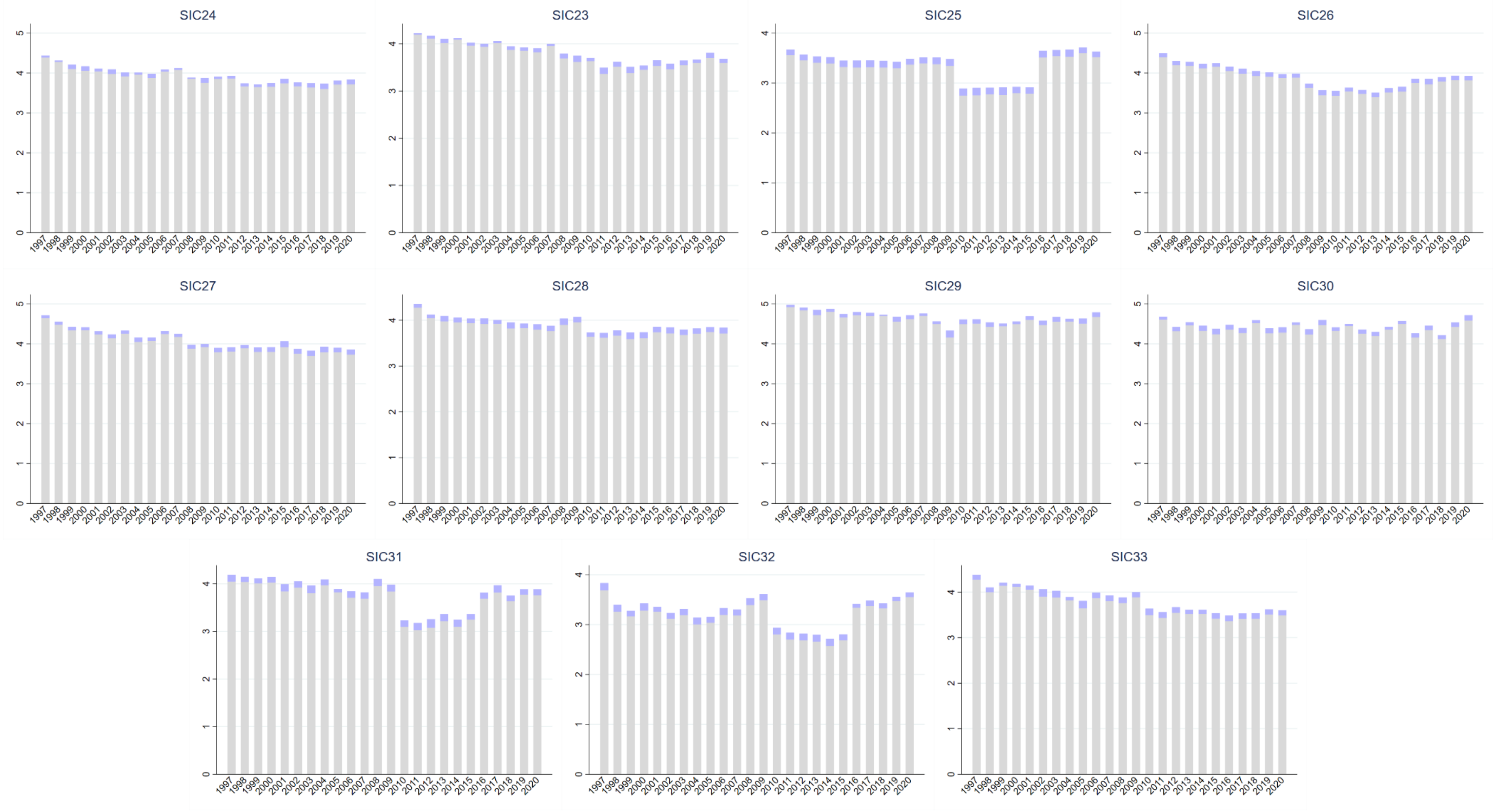


Figure 3. Fixed and Variable Costs in Labour Input

Notes: The fixed component (light blue bars) is estimated through our proposed specification through each SIC2 industry and each year.

Figure 4. Fixed and Variable Costs in Capital Investment in Land and Building (continued)

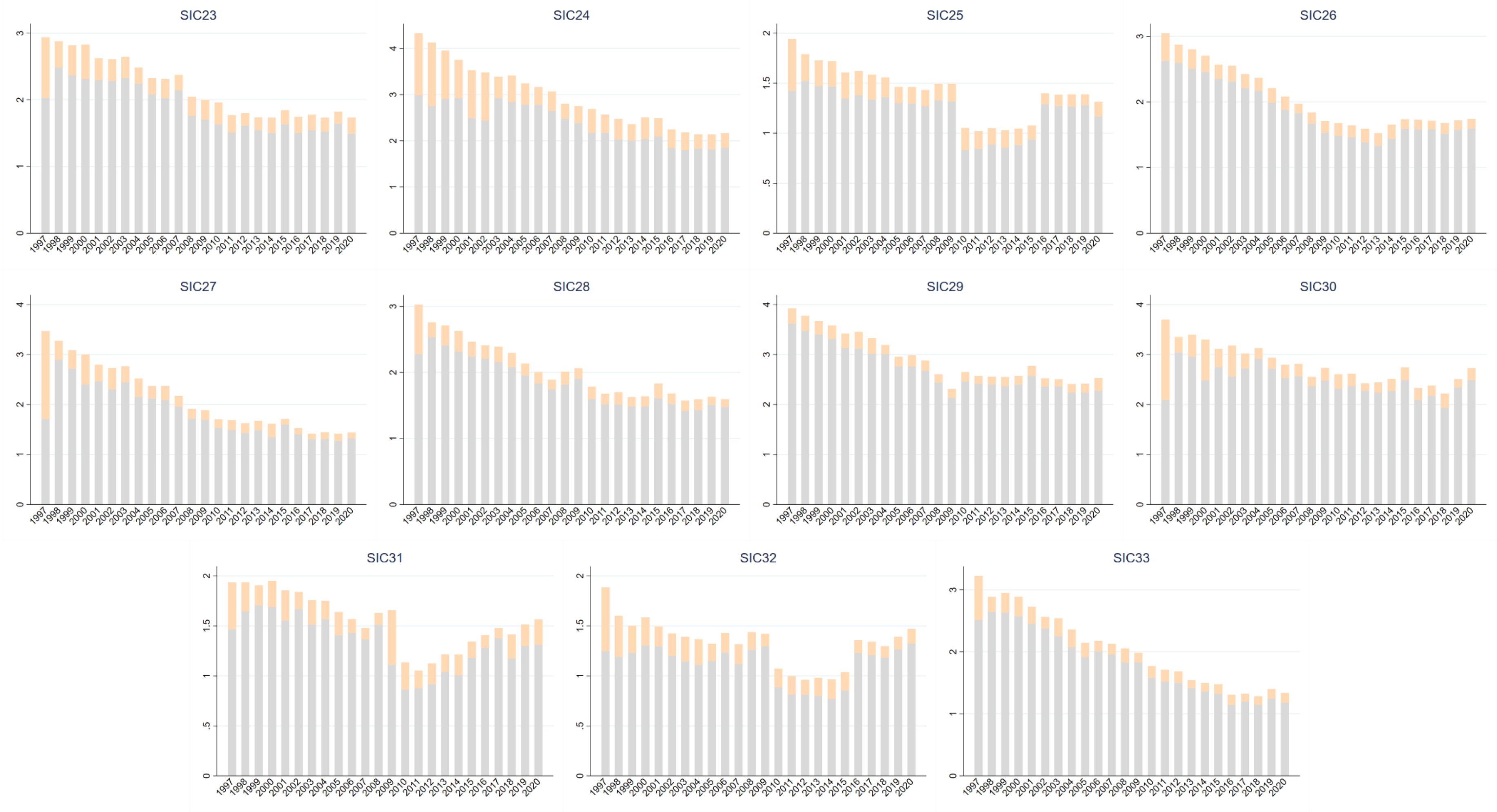


Figure 4. Fixed and Variable Costs in Capital Investment in Land and Building

Notes: The fixed component (light orange bars) is estimated through our proposed specification through each SIC2 industry and each year.

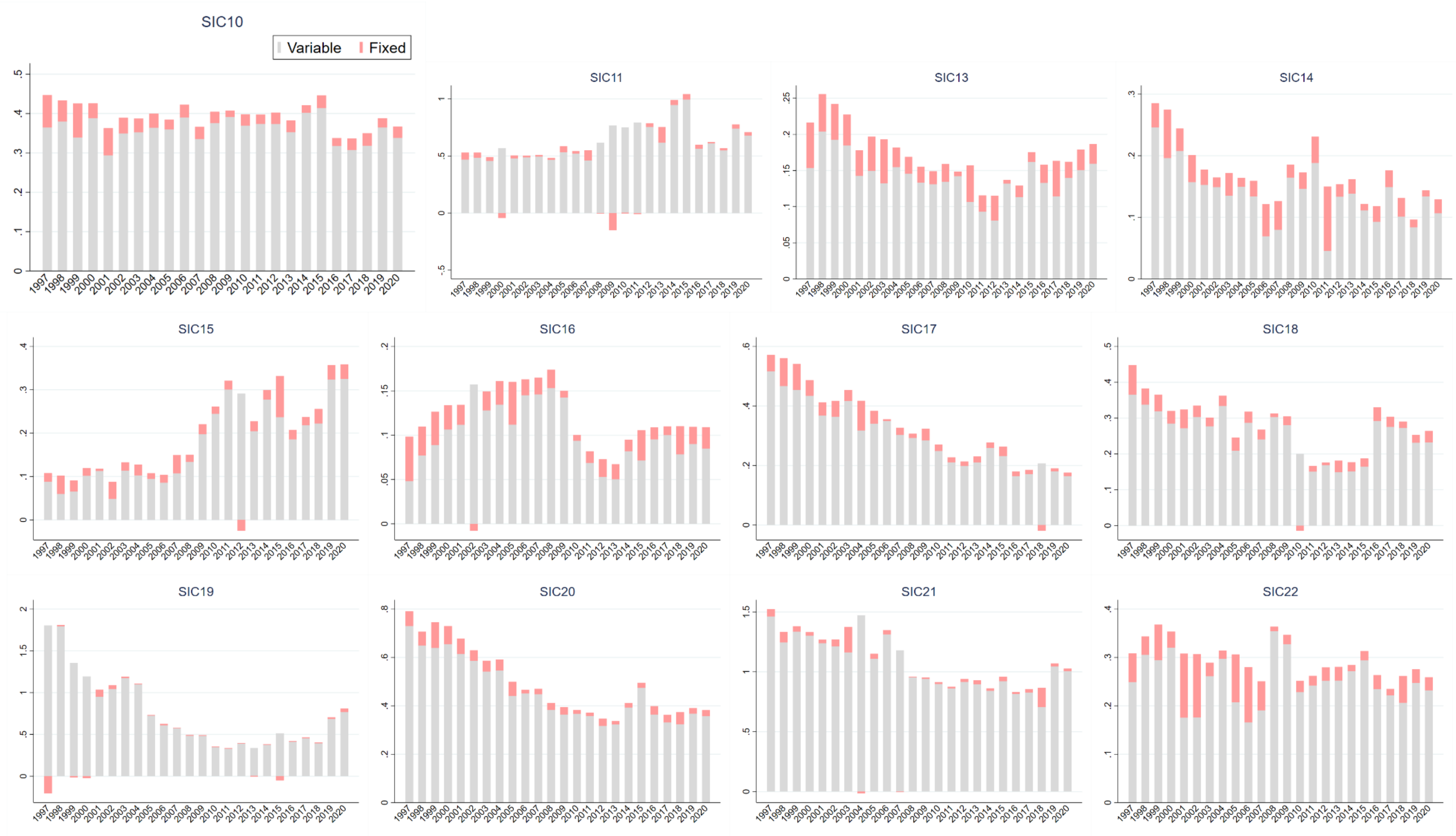


Figure 5. Fixed and Variable Costs in Capital Investment in Software and Database (continued)

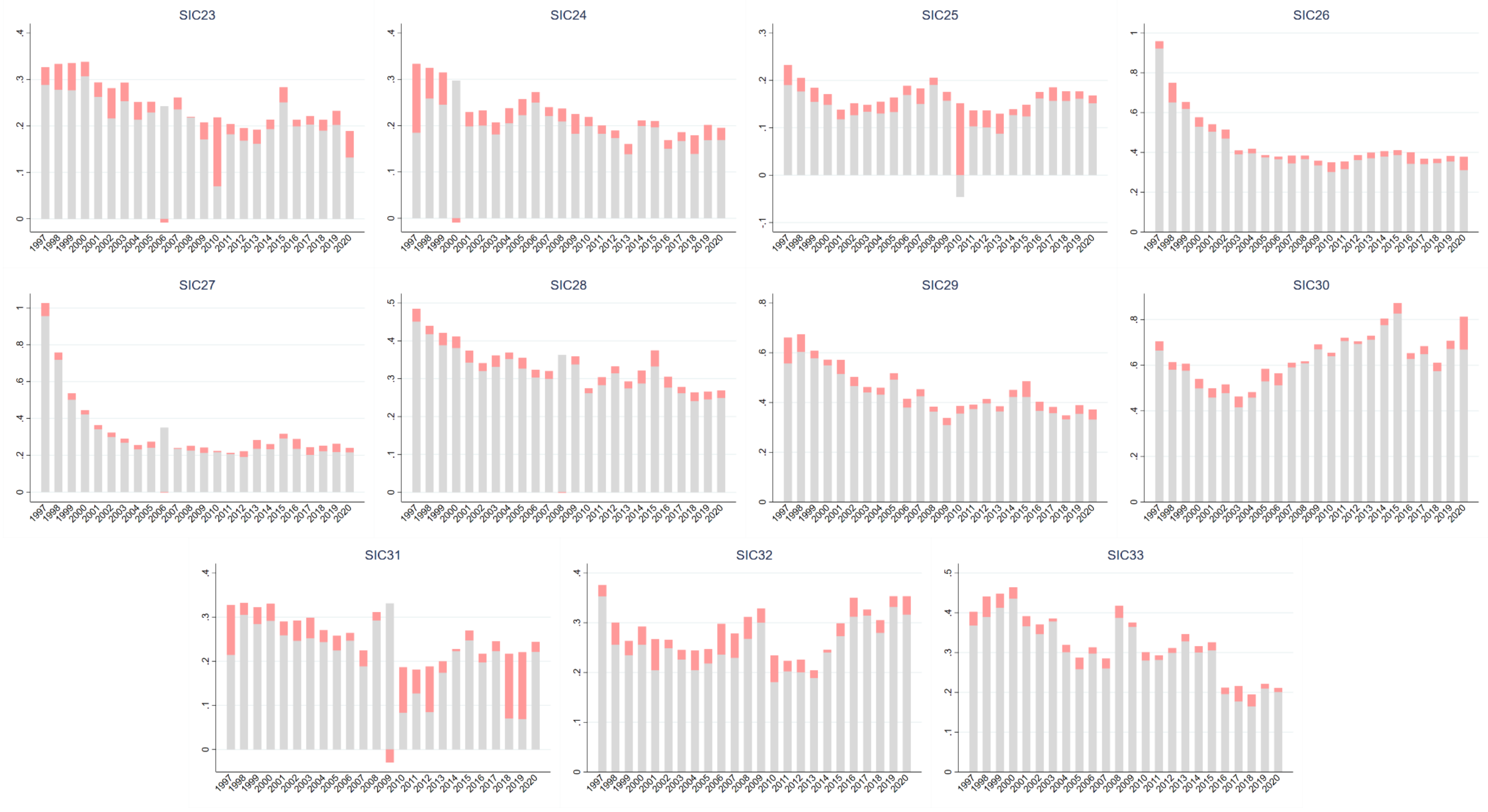


Figure 5. Fixed and Variable Costs in Capital Investment in Software and Database

Notes: The fixed component (light orange bars) is estimated through our proposed specification through each SIC2 industry and each year.

Figure 6. Fixed and Variable Costs in Capital Investment in Others (continued)

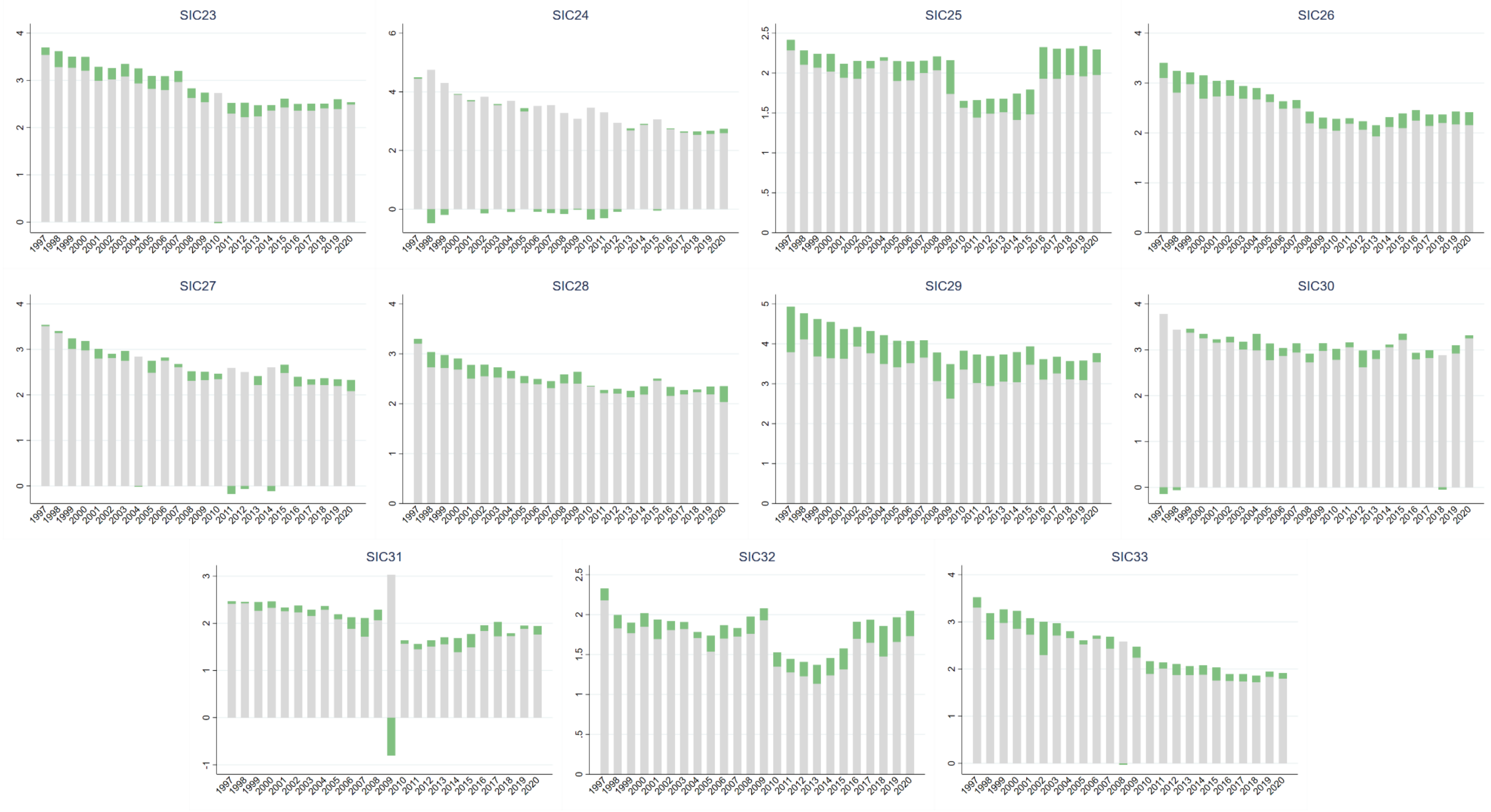


Figure 6. Fixed and Variable Costs in Capital Investment in Others

Notes: The fixed component (light orange bars) is estimated through our proposed specification through each SIC2 industry and each year.

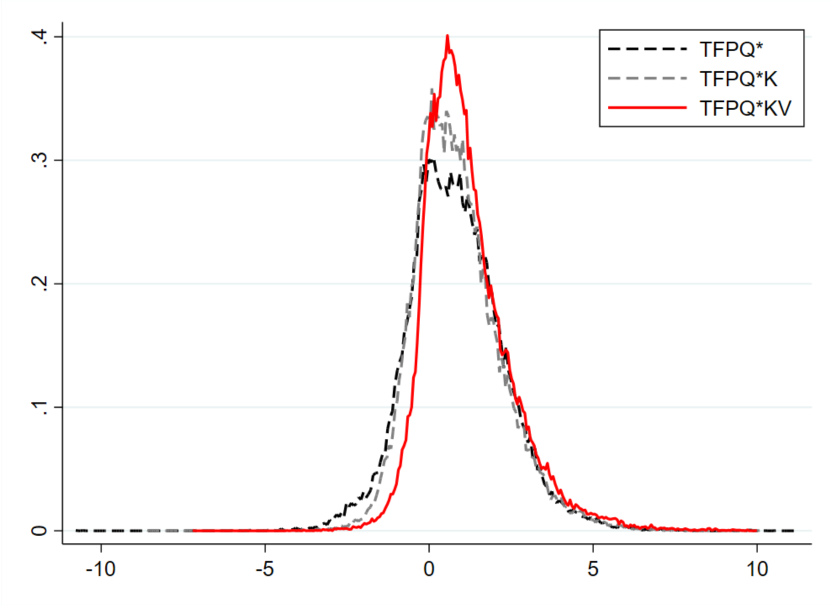


Figure 7. TFP Distribution

Notes: The black dashed line represents the distribution of $TFPQ^{*}$ (without taking into account the heterogeneous capital considerations), the gray dash line represents the distribution of $TFPQ^{*K}$ (accounting for heterogeneous capital, but not fixed-variable cost distinctions), and the red dashed line represents the distribution of $TFPQ^{*KV}$ (incorporating both heterogeneous capital and fixed-variable cost considerations).

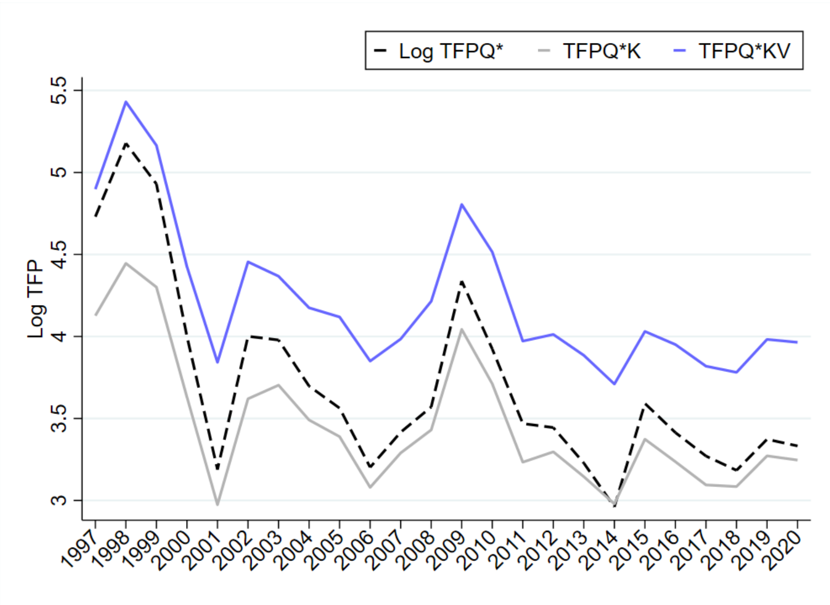
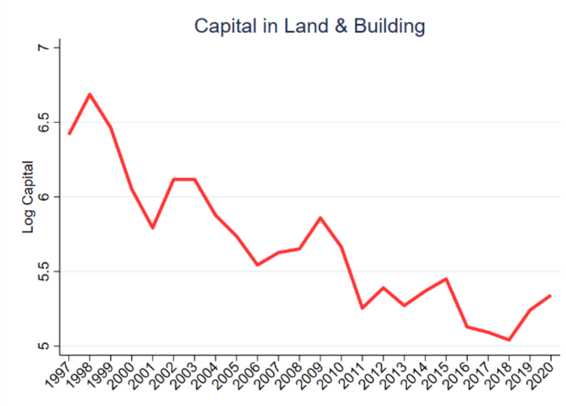


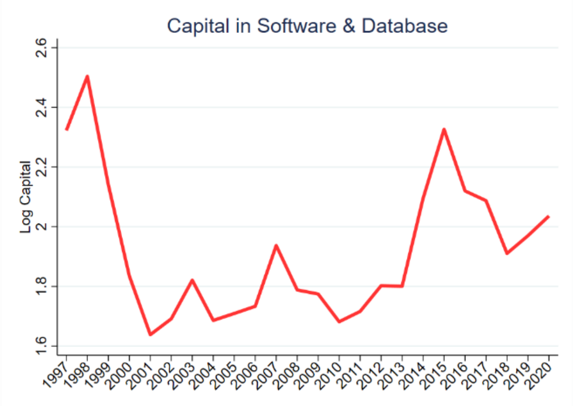
Figure 8. The evolution of TFPQ*, $TFPQ^{*K}$, $TFPQ^{*KV}$

Notes: The figure presents the evolution of TFPQ* (excluding heterogeneous capital considerations, in logarithms) $TFPQ^{*K}$ (accounting for heterogeneous capital but not fixed-variable cost distinctions), and $TFPQ^{*KV}$ (incorporating both heterogeneous capital and fixed-variable cost considerations). TFP measures are weighted by firms' revenue shares.

Panel A Capital in Land and Building



Panel B Capital in Software and Database



Panel C Other Capital

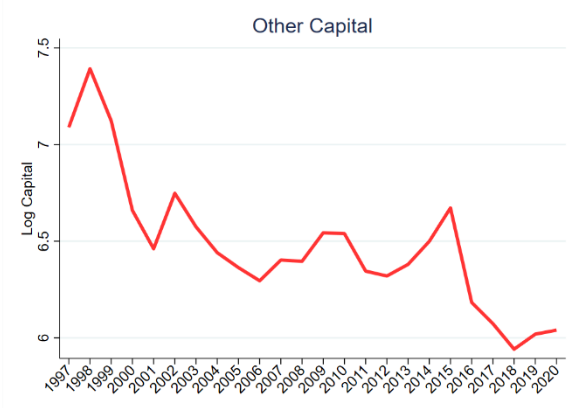
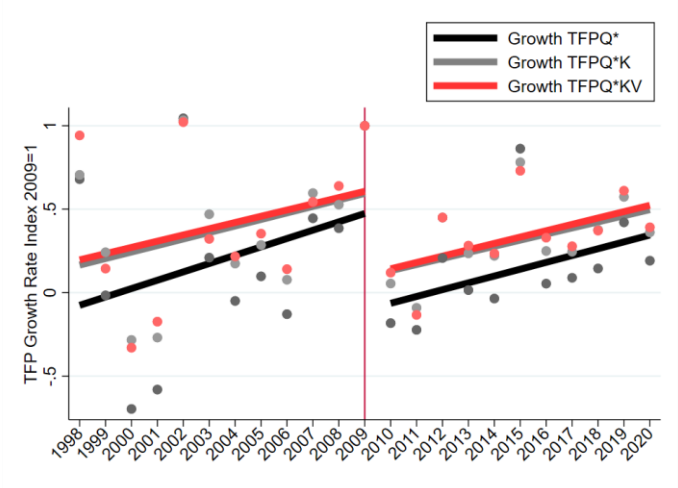


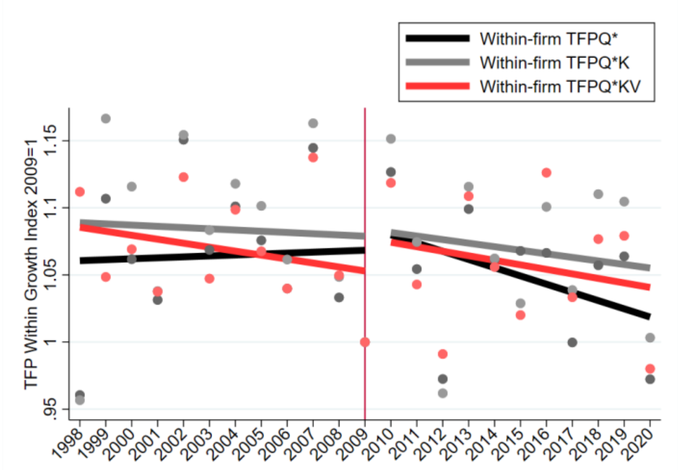
Figure 9. The Evolution of Capital Investment

Notes: Capital investment is measured through firms revenue weighted aggregation in logarithem.

Panel A Growth Index



Panel B Within-Firm Growth Index



Panel C Reallocation Index

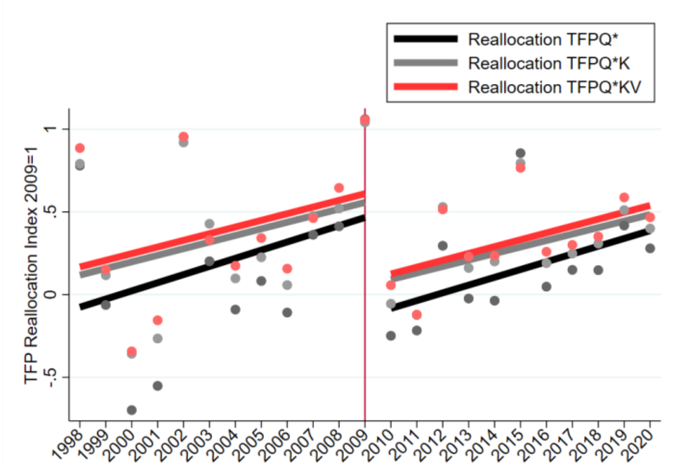


Figure 10. TFP Index, 2009 = 1

Notes: The TFPQ* index shows the evolution of a revenue-share weighted index of TFPQ* between 1998 and 2020, where the value of the index is set equal to 1 in 2009. The decomposition of the index is based on equation (18). The net-entry term is combined into the broad reallocation index.

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