Measuring the Bias of Technological Change*

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Abstract

Technological change can increase the productivity of the various factors of production in equal terms, or it can be biased towards a specific factor. We directly assess the bias of technological change by measuring, at the level of the individual firm, how much of it is labor augmenting and how much is factor neutral. To do so, we develop a framework for estimating production functions when productivity is multi-dimensional. Using panel data from Spain, we find that technological change is biased, with both its labor-augmenting and its factor-neutral components causing output to grow by about 1.5% per year.

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1 Introduction

When technological change occurs, it can increase the productivity of capital, labor, and the other factors of production in equal terms, or it can be biased towards a specific factor. Whether technological change favors some factors of production over others is central to economics. Yet, the empirical evidence is relatively sparse.

The literature on economic growth rests on the assumption that technological change increases the productivity of labor vis-à-vis the other factors of production. It is well known that for a neoclassical growth model to exhibit steady-state growth, either the production function must be Cobb-Douglas or technological change must be labor augmenting (Uzawa 1961), and many endogenous growth models point to human capital accumulation as a source of productivity increases (Lucas 1988, Romer 1990). A number of recent papers provide microfoundations for the literature on economic growth by theoretically establishing that profit-maximizing incentives can ensure that technological change is, at least in the long run, purely labor augmenting (Acemoglu 2003, Jones 2005). Whether this is indeed the case is, however, an empirical question that remains to be answered.

One reason for the scarcity of empirical assessments of the bias of technological change may be a lack of suitable data. Following early work by Brown & de Cani (1963) and David & van de Klundert (1965), economists have estimated aggregate production or cost functions that proxy for labor-augmenting technological change with a time trend (Lucas 1969, Kalt 1978, Antrás 2004, Klump, McAdam & Willman 2007, Binswanger 1974, Cain & Paterson 1986, Jin & Jorgenson 2010). While this line of research has produced some evidence of labor-augmenting technological change, the staggering amount of heterogeneity across firms in combination with simultaneously occurring entry and exit (Dunne, Roberts & Samuelson 1988, Davis & Haltiwanger 1992) may make it difficult to interpret a time trend as a meaningful average economy- or sector-wide measure of technological change. Furthermore, this line of research pays scant attention to the fundamental endogeneity problem in production function estimation. This problem arises because a firm’s decisions depend on its productivity, and productivity is not observed by the econometrician, and may severely bias the estimates (Marschak & Andrews 1944).

While traditionally using more disaggregated data, the productivity and industrial organization literatures assume that technological change is factor neutral. Hicks-neutral technological change underlies, either explicitly or implicitly, most of the standard techniques for measuring productivity, ranging from the classic growth decompositions of Solow (1957) and Hall (1988) to the recent structural estimators for production functions (Olley & Pakes 1996, Levinsohn & Petrin 2003, Ackerberg, Caves & Frazer 2015, Doraszelski & Jaumandreu 2013, Gandhi, Navarro & Rivers 2013).

A much larger literature has estimated the elasticity of substitution using either aggregated or disaggregated data whilst maintaining the assumption of factor-neutral technological change, see Hammermesh (1993) for a survey.
In this paper, we extend the productivity and industrial organization literatures and develop a framework for estimating production functions when productivity is multi-dimensional and has a labor-augmenting and a Hicks-neutral component. We use firm-level panel data that is now widely available to directly assess the bias of technological change by measuring, at the level of the individual firm, how much of technological change is labor augmenting and how much of it is Hicks neutral.

To tackle the endogeneity problem in production function estimation, we build on the insight of Olley & Pakes (1996) that if the decisions that a firm makes can be used to infer its productivity, then productivity can be controlled for in the estimation. We infer the firm’s multi-dimensional productivity from its input usage, in particular its labor and materials decisions. The key to identifying the bias of technological change is that Hicks-neutral technological change scales input usage but, in contrast to labor-augmenting technological change, does not change the mix of inputs that a firm uses. A change in the input mix therefore contains information about the bias of technological change, provided we control for the relative prices of the various inputs and other factors that may change the input mix.

We apply our framework to examine the speed and direction of technological change in the Spanish manufacturing sector in the 1990s and early 2000s. Spain is an attractive setting for two reasons. First, Spain became fully integrated into the European Union between the end of the 1980s and the beginning of the 1990s. Any trends in technological change that our analysis uncovers for Spain may thus be viewed as broadly representative for other continental European economies. Second, Spain inherited an industrial structure with few high-tech industries and mostly small and medium-sized firms. R&D is widely seen as lacking. Yet, Spain grew rapidly during the 1990s, and R&D became increasingly important (European Commission 2001). The accompanying changes in industrial structure are a useful source of variation for analyzing the role of R&D in stimulating different types of technological change.

The particular data set we use has several advantages. The broad coverage allows us to assess the bias of technological change in industries that differ greatly in terms of firms’ R&D activities. The data set also has an unusually long time dimension, enabling us to disentangle trends in technological change from short-term fluctuations. Finally, the data set has firm-level prices that we exploit heavily in the estimation.

The Spanish manufacturing sector also poses several challenges for identifying the bias of technological change from a change in the mix of inputs that a firm uses. First, outsourcing directly changes the input mix as the firm procures customized parts and pieces from its

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2There are other firm-level data sets such as the Colombian Annual Manufacturers Survey (Eslava, Haltiwanger, Kugler & Kugler 2004), the Prowess data collected by the Centre for Monitoring the Indian Economy (De Loecker, Goldberg, Khandelwal & Pavcnik 2016), and the Longitudinal Business Database at the U.S. Census Bureau that contain separate information on prices and quantities, at least for a subset of industries (Roberts & Supina 1996, Foster, Haltiwanger & Syverson 2008, Foster, Haltiwanger & Syverson 2016).
suppliers rather than makes them in house from scratch. Second, the Spanish labor market manifestly distinguishes between permanent and temporary labor. We further contribute to the literature following Olley & Pakes (1996) by accounting for outsourcing and the dual nature of the labor market.

Our estimates provide clear evidence that technological change is biased. Ceteris paribus labor-augmenting technological change causes output to grow, on average, in the vicinity of 1.5% per year. While there is a shift from unskilled to skilled workers in our data, this skill upgrading explains some but not all of the growth of labor-augmenting productivity. In many industries, labor-augmenting productivity grows because workers with a given set of skills become more productive over time.

At the same time, our estimates show that Hicks-neutral technological change plays an equally important role. In addition to labor-augmenting technological change, Hicks-neutral technological change causes output to grow, on average, in the vicinity of 1.5% per year.

Behind these averages lies a substantial amount of heterogeneity across industries and firms. Our estimates point to substantial and persistent differences in labor-augmenting and Hicks-neutral productivity across firms, in line with the “stylized facts” about productivity in Bartelsman & Doms (2000) and Syverson (2011). Beyond these facts, we show that, at the level of the individual firm, the levels of labor-augmenting and Hicks-neutral productivity are positively correlated, as are their rates of growth.

Our estimates further indicate that firms’ R&D activities play a key role in determining the differences in the components of productivity across firms and their evolution over time. Interestingly, labor-augmenting productivity is slightly more closely tied to firms’ R&D activities than is Hicks-neutral productivity. Through the lens of the literature on induced innovation and directed technical change (Hicks 1932, Acemoglu 2002), this may be viewed as supporting the argument that firms direct their R&D activities to conserve on labor.

Biased technological change has consequence far beyond the growth of output. To illustrate, we use our estimates to show that biased technological change is the primary driver of the decline of the aggregate share of labor in the Spanish manufacturing sector over our sample period. Similar declines have been observed in many advanced economies in past decades and have attracted considerable attention in the macroeconomics literature (Blanchard 1997, Bentolila & Saint-Paul 2004, McAdam & Willman 2013, Karabarbounis & Neiman 2014, Oberfield & Raval 2014).

The starting point of this paper are the recent structural estimators for production functions. We differ from much of the previous literature by exploiting the parameter restrictions between the production and input demand functions, as in Doraszelski & Jaumandreu (2013). This allows us to parametrically invert from observed input usage to unobserved productivity and eases the demands on the data compared to the nonparametric inversion in Olley & Pakes (1996), Levinsohn & Petrin (2003), and Ackerberg et al. (2015), especially
if the input demand functions are high-dimensional\footnote{See Doraszelski & Jaumandreu (2013) for details on the pros and cons of the parametric inversion.}

Our paper is related to Van Biesebroeck (2003). Using plant-level panel data for the U.S. automobile industry, he estimates a plant’s Hicks-neutral productivity as a fixed effect and parametrically inverts from the plant’s input usage to its capital-biased (also called labor-saving) productivity. Our approach is more general in that we allow all components of productivity to evolve over time and in response to firms’ R&D activities.

Our paper is further related to Grieco, Li & Zhang (2016) and subsequent work in progress by Zhang (2015). Because their data contains the materials bill rather than its split into price and quantity, Grieco et al. (2016) build on Doraszelski & Jaumandreu (2013) and parametrically invert from a firm’s input usage to its Hicks-neutral productivity and the price of materials that the firm faces.

Finally, our paper touches—although more tangentially—on the literature on skill bias that studies the differential impact of technological change, especially in the form of computerization, on the various types of labor (see Card & DiNardo (2002) and Violante (2008) and the references therein). While we focus on labor versus the other factors of production, the techniques we develop may be adapted to investigate the skill bias of technological change, although our particular data set is not ideal for this purpose.

The remainder of this paper is organized as follows: Section 2 explains how we identify the bias of technological change and previews our empirical strategy. Section 3 describes the data and some patterns in the data that inform the subsequent analysis. Section 4 sets out a dynamic model of the firm. Section 5 develops an estimator for production functions when productivity is multi-dimensional. Sections 6–9 present our main results on labor-augmenting and Hicks-neutral technological change. Section 10 explores whether capital-augmenting technological change plays a role in our data in addition to labor-augmenting and Hicks-neutral technological change. Section 11 concludes. An Online Appendix contains additional results and technical details.

Throughout the paper, we adopt the convention that uppercase letters denote levels and lowercase letters denote logs. Unless noted otherwise, we refer to output and the various factors of production in terms of quantity and not in terms of value. In particular, we refer to the value of labor as the wage bill and to the value of materials as the materials bill.

2 Labor-augmenting and Hicks-neutral productivity

We first show how to separately recover a firm’s labor-augmenting and Hicks-neutral productivity from its labor and materials decisions. Then we show that the constant elasticity of substitution (CES) production function that we use in our application approximates, to a first order, the relationship between the input mix and labor-augmenting productivity that arises in a wider class of production functions. To facilitate the exposition, we proceed
in a highly simplified setting. Our application extends the setting to accommodate the institutional realities of the Spanish manufacturing sector.

Consider a firm with the production function

$$Y_{jt} = F(K_{jt}, \exp(\omega_{Ljt})L_{jt}, M_{jt}) \exp(\omega_{Hjt}) \exp(e_{jt}),$$

(1)

where $Y_{jt}$ is the output of firm $j$ in period $t$, $K_{jt}$ is capital, $L_{jt}$ is labor, and $M_{jt}$ is materials. The labor-augmenting productivity of firm $j$ in period $t$ is $\omega_{Ljt}$ and its Hicks-neutral productivity is $\omega_{Hjt}$. Finally, $e_{jt}$ is a random shock.

To relate the input ratio $\frac{M_{jt}}{L_{jt}}$ to labor-augmenting productivity $\omega_{Ljt}$, we assume that $(\exp(\omega_{Ljt})L_{jt}, M_{jt})$ is separable from $K_{jt}$ in that the function $F(\cdot)$ in equation (1) is composed of the functions $G(\cdot)$ and $H(\cdot)$ as

$$F(K_{jt}, \exp(\omega_{Ljt})L_{jt}, M_{jt}) = G(K_{jt}, H(\exp(\omega_{Ljt})L_{jt}, M_{jt}))),$$

(2)

where $H(\exp(\omega_{Ljt})L_{jt}, M_{jt})$ is homogeneous of arbitrary degree. Without loss of generality, we set the degree of homogeneity to one. Throughout we maintain that all functions are differentiable as needed. As in Levinsohn & Petrin (2003), we finally assume that labor and materials are static (or “variable”) inputs that are chosen each period to maximize short-run profits and that the firm is a price-taker in input markets, where it faces $W_{jt}$ and $P_{Mjt}$ as prices of labor and materials, respectively.

The input ratio $\frac{M_{jt}}{L_{jt}}$ is therefore the solution to the ratio of the first-order conditions for labor and materials

$$\frac{\partial H(\exp(\omega_{Ljt})L_{jt}, M_{jt})}{\partial L_{jt}} \frac{\exp(\omega_{Ljt})}{\partial H(\exp(\omega_{Ljt})L_{jt}, M_{jt})} = \frac{\partial H(\exp(\omega_{Ljt})-(m_{jt}-l_{jt}), 1)}{\partial L_{jt}} \frac{\exp(\omega_{Ljt})}{\partial H(\exp(\omega_{Ljt})-(m_{jt}-l_{jt}), 1)} = \frac{W_{jt}}{P_{Mjt}},$$

(3)

where the first equality uses that $H(\exp(\omega_{Ljt})L_{jt}, M_{jt})$ is homogeneous of degree one and, recall, uppercase letters denote levels and lowercase letters denote logs.

Equation (3) implies that the input ratio $\frac{M_{jt}}{L_{jt}}$ depends on the price ratio $\frac{P_{Mjt}}{W_{jt}}$ and labor-augmenting productivity $\omega_{Ljt}$. Importantly, the input ratio $\frac{M_{jt}}{L_{jt}}$ does not depend on Hicks-neutral productivity $\omega_{Hjt}$. This formalizes that the mix of inputs that a firm uses is related to—and therefore contains information about—its labor-augmenting productivity but is unrelated to its Hicks-neutral productivity. Intuitively, the labor and materials decisions hinge on the marginal products of labor and materials. Because the marginal products are proportional to Hicks-neutral productivity, materials per unit of labor as determined by the ratio of the first-order conditions in equation (3) is unrelated to Hicks-neutral productivity.

4Equation (2) immediately implies that $F(K_{jt}, \exp(\omega_{Ljt})L_{jt}, M_{jt})$ is weakly separable in the partition $(K_{jt}, (\exp(\omega_{Ljt})L_{jt}, M_{jt}))$ (Chambers 1988, equation (1.26)). It is equivalent to $F(K_{jt}, \exp(\omega_{Ljt})L_{jt}, M_{jt})$ being weakly separable under some additional monotonicity and quasi-concavity assumptions (Goldman & Uzawa 1964).
In this sense, separating labor-augmenting from Hicks-neutral productivity does not rely on functional form beyond the separability assumption in equation (2).

The following proposition further characterizes the log of the input ratio $m_{jt} - l_{jt}$:

**Proposition 1** The input ratio $m_{jt} - l_{jt}$ has the first-order Taylor series

$$
\gamma_0^L - \sigma (\exp(\omega^0_{Ljt} - (m^0_{jt} - l^0_{jt}))) (p_{Mjt} - w_{jt}) + (1 - \sigma (\exp(\omega^0_{Ljt} - (m^0_{jt} - l^0_{jt})))) \omega_{Ljt}
$$

around a point $(m^0_{jt} - l^0_{jt}, p^0_{Mjt} - w^0_{jt}, \omega^0_{Ljt})$ satisfying equation (3), where $\gamma_0^L$ is a constant and $\sigma \left( \exp(\omega^0_{Ljt} - (m^0_{jt} - l^0_{jt})) \right)$ is the elasticity of substitution between materials and labor in the production function in equation (1).

The proof can be found in Appendix A.

Our application uses a CES production function

$$
Y_{jt} = \left[ \beta_K K_{jt}^{-\frac{1-\sigma}{\sigma}} + (\exp(\omega_{Ljt}L_{jt})L_{jt})^{-\frac{1-\sigma}{\sigma}} + \beta_M M_{jt}^{-\frac{1-\sigma}{\sigma}} \right]^{-\frac{\nu}{1-\sigma}} \exp(\omega_{Hjt}) \exp(e_{jt}),
$$

where $\nu$ and $\sigma$ are the elasticity of scale and substitution, respectively, and $\beta_K$ and $\beta_M$ are the so-called distributional parameters. Depending on the elasticity of substitution, the CES production function encompasses the special cases of a Leontieff ($\sigma \rightarrow 0$), Cobb-Douglas ($\sigma = 1$), and linear ($\sigma \rightarrow \infty$) production function.

The ratio of the first-order conditions in equation (3) implies

$$
m_{jt} - l_{jt} = \sigma \ln \beta_M - \sigma (p_{Mjt} - w_{jt}) + (1 - \sigma) \omega_{Ljt}.
$$

Comparing equations (4) and (5) shows that the CES production function approximates, to a first order, the input ratio $m_{jt} - l_{jt}$ arising from an arbitrary production function satisfying equation (2). This gives a sense of robustness to the CES production function.

Our empirical strategy uses equation (5) to recover a firm’s labor-augmenting productivity from its input mix. In doing so, we must control for other factors besides the relative prices of the various inputs that may change the input mix, in particular outsourcing and the dual nature of the Spanish labor market. With labor-augmenting productivity in hand,

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*One can forgo the separability assumption by relying more on functional form. Our empirical strategy generalizes to, for example, a translog production function that does not satisfy equation (2).*

*We implicitly set the constant of proportionality $\beta_0$ to one because it cannot be separated from an additive constant in Hicks-neutral productivity $\omega_{Hjt}$. We estimate them jointly and carefully ensure that the reported results depend only on their sum. We similarly normalize the distributional parameter $\beta_L$. Technological change can therefore equivalently be thought of as letting these parameters of the production function vary by firm and time. The nascent literature on heterogeneous production functions (Balat, Brambilla & Sasaki 2015, Fox, Hadad, Hoderlein, Petrin & Sherman 2016, Kasahara, Schrmpf & Suzuki 2015) explores to what extent it is possible to let all parameters of the production function vary by firm and time.*

*It also suggests that our “nonparametric” estimates of labor-augmenting technological change can be fed into a growth decomposition along the lines of Solow (1957) and Hall (1988) to obtain a “nonparametric” estimate of Hicks-neutral technological change. We leave this to future research.*

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we use the first-order condition for labor to recover Hicks-neutral productivity. The remainder of our empirical strategy follows along the lines of Olley & Pakes (1996), Levinsohn & Petrin (2003), Ackerberg et al. (2015), and Doraszelski & Jaumandreu (2013) by combining the inferred productivities with their laws of motion to set up estimation equations.

Equation (5) has a long tradition in the literature, although it is used in a very different way from ours. With skilled and unskilled workers in place of materials and labor, equation (5) is at the heart of the literature on skill bias (Card & DiNardo 2002, Violante 2008). With capital in place of materials, equation (5) serves to estimate the elasticity of substitution $\sigma$ in an aggregate value-added production function (see Antràs 2004). More recently, Raval (2013) uses a variant of equation (5) obtained from a value-added production function with capital- and labor-augmenting productivity to estimate $\sigma$ from firm-level panel data.

Equation (5) is typically estimated by OLS. The problem is that labor-augmenting productivity, which is not observed by the econometrician, is correlated over time and also with the wage. We intuitively expect the wage to be higher when labor is more productive, even if it adjusts slowly with some lag. This positive correlation induces an upward bias in the estimate of the elasticity of substitution. This is a variant of the endogeneity problem in production function estimation. Because we use equation (5) to recover labor-augmenting productivity rather than directly estimate it, we are able tackle the endogeneity problem with a combination of assumptions on the timing of decisions and the evolution of the components of productivity.

3 Data

Our data comes from the Encuesta Sobre Estrategias Empresariales (ESEE) survey, a firm-level survey of the Spanish manufacturing sector sponsored by the Ministry of Industry, and spans 1990 to 2006. At the beginning of the survey, 5% of firms with up to 200 workers were sampled randomly by industry and size strata. All firms with more than 200 workers were asked to participate in the survey, and 70% of them complied. Some firms vanish from the sample due to either exit (shutdown by death or abandonment of activity) or attrition. These reasons can be distinguished in the data and attrition remained within acceptable limits. To preserve representativeness, newly created firms were added to the sample every year. We provide details on industry and variable definitions in Appendix B.

Our sample covers a total of 2375 firms in ten industries when restricted to firms with at least three years of data. Columns (1) and (2) of Table I show the number of observations and firms by industry. Sample sizes are moderate. Newly created firms are a large fraction of the total number of firms, ranging from 26% to 50% in the different industries. There is a much smaller fraction of exiting firms, ranging from 6% to 15% and above in a few industries.

The 1990s and early 2000s were a period of rapid output growth, coupled with stagnant
or, at best, slightly increasing employment and intense investment in physical capital, see columns (3)–(6) of Table 1. Consistent with this rapid growth, firms on average report that their markets are slightly more often expanding rather than contracting; hence, demand tends to shift out over time.

An attractive feature of our data is that it contains firm-specific, Paasche-type price indices for output and materials. We note that the variation in these price indices is partly due to changes over time in the bundles of goods that make up output and, respectively, materials (see Bernard, Redding & Schott (2010) and Goldberg, Khandelwal, Pavcnik & Topalova (2010) for evidence on product turnover), and that these changes may be related to a firm’s productivity. The growth of prices, averaged from the growth of prices as reported individually by each firm, is moderate. The growth of the price of output in column (7) ranges from 0.8% to 2.1%. The growth of the wage ranges from 4.3% to 5.4% and the growth of the price of materials ranges from 2.8% to 4.1%.

**Biased technological change.** The evolution of the relative quantities and prices of the various factors of production already hints at an important role for labor-augmenting technological change. As columns (8) and (9) of Table 1 show, with the exception of industries 7, 8, and 9, the input ratio \( \frac{M_{jt}}{L_{jt}} \) increases much more than the price ratio \( \frac{P_{Mjt}}{W_{jt}} \) decreases. One possible explanation is that the elasticity of substitution between materials and labor exceeds 1. To see this, recall that the elasticity of substitution (Chambers 1988, equation (1.12)) is

\[
\frac{d \ln \left( \frac{M_{jt}}{L_{jt}} \right)}{d \ln \left( |MRTS_{MLjt}| \right)} = \frac{d \ln \left( \frac{M_{jt}}{L_{jt}} \right)}{d \ln \left( \frac{P_{Mjt}}{W_{jt}} \right)},
\]

where \( |MRTS_{MLjt}| \) is the absolute value of the marginal rate of technological substitution between materials and labor, and the equality follows to the extent that it equals the price ratio \( \frac{P_{Mjt}}{W_{jt}} \). However, because the estimates of the elasticity of substitution in the previous literature lie somewhere between 0 and 1 (see Chirinko (2008) and the references therein for the elasticity of substitution between capital and labor and Bruno (1984), Rotemberg & Woodford (1996), and Oberfield & Raval (2014) for the elasticity of substitution between materials and an aggregate of capital and labor), this explanation is implausible. Labor-augmenting technological change offers an alternative explanation. As it makes labor more productive, equation (4) implies that it directly increases materials per unit of labor. Thus, labor-augmenting technological change may go a long way in rationalizing why the change in the input ratio \( \frac{M_{jt}}{L_{jt}} \) exceeds the change in the price ratio \( \frac{P_{Mjt}}{W_{jt}} \).

In contrast, columns (10) and (11) of Table 1 provide no evidence for capital-augmenting technological change. The investment boom in Spain in the 1990s and early 2000s was fueled by improved access to European and international capital markets. With the exception of industries 5, 6, and 8, the concomitant decrease in the input ratio \( \frac{M_{jt}}{K_{jt}} \) is much smaller than
the increase in the price ratio $\frac{P_{Mjt}}{P_{Kjt}}$, where $P_{Kjt}$ is the price of capital as however roughly measured by the user cost in our data. This pattern is consistent with an elasticity of substitution between materials and capital between 0 and 1. Indeed, capital-augmenting technological change can only directly contribute to the decline in materials per unit of capital in the unlikely scenario that it makes capital less productive.

Based on these patterns in the data we focus on labor-augmenting technological change in the subsequent analysis. We return to capital-augmenting technological change in Section 10. In the remainder of this section we point out other features of the data that figure prominently in our analysis.

**Temporary labor.** We distinguish between permanent and temporary labor and treat temporary labor as a static input that is chosen each period to maximize short-run profits. This is appropriate because Spain greatly enhanced the possibilities for hiring and firing temporary workers during the 1980s, and by the beginning of the 1990s had one the highest shares of temporary workers in Europe (Dolado, Garcia-Serrano & Jimeno 2002). Temporary workers are employed for fixed terms with no or very small severance pay. In our sample, between 72% and 84% of firms use temporary labor and, among the firms that do, its share of the labor force ranges from 16% in industry 10 to 32% in industry 9, see columns (1) and (2) of Table 2.

Rapid expansions and contractions of temporary labor are common: The difference between the maximum and the minimum share of temporary labor within a firm ranges on average from 20% to 33% across industries (column (3)). In addition to distinguishing temporary from permanent labor, we measure labor as hours worked (see Appendix B). At this margin, firms enjoy a high degree of flexibility: Within a firm, the difference between the maximum and the minimum hours worked ranges on average from 43% to 56% across industries, and the difference between the maximum and the minimum hours per worker ranges on average from 4% to 13% (columns (4) and (5)).

**Outsourcing.** Outsourcing may directly contribute to the shift from labor to materials that column (8) of Table 1 documents as firms procure customized parts and pieces from their suppliers rather than make them in house from scratch. As can be seen in columns (6) and (7) of Table 2, between 21% and 57% of firms in our sample engage in outsourcing. Among the firms that do, the share of outsourcing in the materials bill ranges from 14% in industry 7 to 29% in industry 4. While the share of outsourcing remains stable over our sample period, the standard deviation in column (7) indicates a substantial amount of heterogeneity across the firms within an industry, similar to the share of temporary labor in column (2).

**Firms’ R&D activities.** Columns (8)–(10) of Table 2 show that the ten industries differ markedly in terms of firms’ R&D activities and that there is again substantial heterogeneity
across the firms within an industry. Industries 3, 4, 5, and 6 exhibit high innovative activity. More than two-thirds of firms perform R&D during at least one year in the sample period, with at least 36% of stable performers engaging in R&D in all years (column (8)) and at least 28% of occasional performers engaging in R&D in some but not all years (column (9)). The R&D intensity among performers ranges on average from 2.2% to 2.9% (column (10)). Industries 1, 2, 7, and 8 are in an intermediate position. Less than half of firms perform R&D, and there are fewer stable than occasional performers. The R&D intensity is on average between 1.1% and 1.7% with a much lower value of 0.7% in industry 7. Finally, industries 9 and 10 exhibit low innovative activity. About a third of firms perform R&D, and the R&D intensity is on average between 1.0% and 1.5%.

4 A dynamic model of the firm

The purpose of our model is to enable us to infer a firm’s productivity from its input usage and to clarify our assumptions on the timing of decisions that we rely on in estimation.

Production function. The firm has the CES production function

\[ Y_{jt} = \left[ \beta_K K_{jt}^{-\frac{1-\sigma}{\sigma}} + \left( \exp(\omega_{Ljt}) L_{jt}^* \right)^{-\frac{1-\sigma}{\sigma}} + \beta_M \left( M_{jt}^* \right)^{-\frac{1-\sigma}{\sigma}} \right]^{-\frac{1}{1-\sigma}} \exp(\omega_{Hjt}) \exp(e_{jt}), \]  

where \( Y_{jt} \) is the output of firm \( j \) in period \( t \), \( K_{jt} \) is capital, \( \omega_{Ljt} \) is labor-augmenting productivity, \( \omega_{Hjt} \) is Hicks-neutral productivity, and \( e_{jt} \) is a mean zero random shock that is uncorrelated over time and across firms. Extending the setting in Section 2, \( L_{jt}^* = \Lambda(L_{Pjt}, L_{Tjt}) \) is an aggregate of permanent labor \( L_{Pjt} \) and temporary labor \( L_{Tjt} \) and \( M_{jt}^* = \Gamma(M_{Ijt}, M_{Ojt}) \) is an aggregate of in-house materials \( M_{Ijt} \) and outsourced materials (customized parts and pieces) \( M_{Ojt} \). The aggregators \( \Lambda(L_{Pjt}, L_{Tjt}) \) and \( \Gamma(M_{Ijt}, M_{Ojt}) \) accommodate differences in the productivities of permanent and temporary labor, respectively, in-house and outsourced materials.

The production function in equation (6) is the most parsimonious we can use to separate labor-augmenting from Hicks-neutral productivity. It encompasses three restrictions. First, technological change does not affect the parameters \( \nu \) and \( \sigma \), as we are unaware of evidence suggesting that the elasticity of scale or the elasticity of substitution varies over our sample period. Second, the elasticity of substitution between capital, labor, and materials is the same. We assess this restriction in Section 8. For now we note that previous estimates of the elasticity of substitution between materials and an aggregate of capital and labor (Bruno 1984, Rotemberg & Woodford 1996, Oberfield & Raval 2014) fall in the same range as estimates of the elasticity of substitution between capital and labor (Chirinko 2008). Third, the productivities of capital and materials are restricted to change at the same rate.

\footnote{The elasticity of substitution between \( L_{Pjt} \) and \( L_{Tjt} \), respectively, \( M_{Ijt} \) and \( M_{Ojt} \) depends on the aggregators \( \Lambda(L_{Pjt}, L_{Tjt}) \) and \( \Gamma(M_{Ijt}, M_{Ojt}) \) and may differ from \( \sigma \).}
and in lockstep with Hicks-neutral technological change. Treating capital and materials the same is in line with the fact that both are, at least to a large extent, produced goods. In contrast, labor is traditionally viewed as unique among the various factors of production, and changes in its productivity are a tenet of the literature on economic growth. The patterns in the data described in Section 3 further justify focusing on labor-augmenting technological change.

**Laws of motion: Productivity.** The components of productivity are presumably correlated with each other and over time and possibly also correlated across firms. As in Doraszelski & Jaumandreu (2013), we endogenize productivity by incorporating R&D expenditures into the model. We assume that the evolution of the components of productivity is governed by controlled first-order, time-inhomogeneous Markov processes with transition probabilities 

\[ P_{Lt+1}(\omega_{Lt+1} | \omega_{Lt}, R_{jt}) \] and 

\[ P_{Ht+1}(\omega_{Ht+1} | \omega_{Ht}, R_{jt}) \],

where \( R_{jt} \) is R&D expenditures. Despite their parsimony, these stochastic processes accommodate correlation between the components of productivity. Moreover, because they are time-inhomogeneous, they accommodate secular trends in productivity.

The firm knows its current productivity when it makes its decisions for period \( t \) and anticipates the effect of R&D on its future productivity. The Markovian assumption implies

\[ \omega_{Lt+1} = E_t[\omega_{Lt+1} | \omega_{Lt}, R_{jt}] + \xi_{Lt+1} = g_{Lt}(\omega_{Lt}, R_{jt}) + \xi_{Lt+1}, \]

\[ \omega_{Ht+1} = E_t[\omega_{Ht+1} | \omega_{Ht}, R_{jt}] + \xi_{Ht+1} = g_{Ht}(\omega_{Ht}, R_{jt}) + \xi_{Ht+1}. \]

That is, actual labor-augmenting productivity \( \omega_{Lt+1} \) in period \( t + 1 \) decomposes into expected labor-augmenting productivity \( g_{Lt}(\omega_{Lt}, R_{jt}) \) and a random shock \( \xi_{Lt+1} \). This productivity innovation is by construction mean independent (although not necessarily fully independent) of \( \omega_{Lt} \) and \( R_{jt} \). It captures the uncertainties that are naturally linked to productivity as well as those that are inherent in the R&D process such as chance of discovery, degree of applicability, and success in implementation. Nonlinearities in the link between R&D and productivity are captured by the conditional expectation function \( g_{Lt}(\cdot) \) that we estimate nonparametrically along with the parameters of the production function. Actual Hicks-neutral productivity \( \omega_{Ht+1} \) decomposes similarly.

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9A production function with capital-augmenting, labor-augmenting, and materials-augmenting productivity that is homogeneous of arbitrary degree is equivalent to a production function with capital-augmenting, labor-augmenting, and Hicks-neutral productivity. Without loss of generality, we therefore subsume the common component of capital-augmenting, labor-augmenting, and materials-augmenting technological change into Hicks-neutral productivity.

10Our empirical strategy generalizes to a joint Markov process \( P_{t+1}(\omega_{Lt+1}, \omega_{Ht+1} | \omega_{Lt}, \omega_{Ht}, r_{jt}) \). While R&D is widely seen as a major source of productivity growth (Griliches 1998), our empirical strategy extends to other sources such as technology adoption, learning-by-importing (Kasahara & Rodrigue 2008), and learning-by-exporting (De Loecker 2013). Both extensions are demanding on the data, however, as they increase the dimensionality of the functions that must be nonparametrically estimated.
Laws of motion: Capital. Capital accumulates according to $K_{jt+1} = (1 - \delta)K_{jt} + I_{jt}$, where $\delta$ is the rate of depreciation. As in Olley & Pakes (1996), investment $I_{jt}$ chosen in period $t$ becomes effective in period $t + 1$. Choosing $I_{jt}$ is therefore equivalent to choosing $K_{jt+1}$.

Permanent labor. Permanent labor is subject to convex adjustment costs $C_{L_{jt}}(L_{jt}, L_{jt-1})$ that reflect the substantial cost of hiring and firing that the firm may incur (Hamermesh 1993). The choice of permanent labor thus may have dynamic implications. In contrast, temporary labor is a static input.

Outsourcing. Outsourcing is, to a large extent, based on contractual relationships between the firm and its suppliers (Grossman & Helpman 2002, Grossman & Helpman 2005). The ratio of outsourced to in-house materials $Q_{M_{jt}} = \frac{M_{O_{jt}}}{M_{I_{jt}}}$ is subject to (convex or not) adjustment costs $C_{Q_{M_{jt}}}(Q_{M_{jt+1}}, Q_{M_{jt}})$ that stem from forming and dissolving these relationships. The firm must maintain $Q_{M_{jt}}$ but may scale $M_{I_{jt}}$ and $M_{O_{jt}}$ up or down at will; in-house materials, in particular, is a static input.

Output and input markets. The firm has market power in the output market, e.g., because products are differentiated. Its inverse residual demand function $P(Y_{jt}, D_{jt})$ depends on its output $Y_{jt}$ and the demand shifter $D_{jt}$. The firm is a price-taker in input markets, where it faces $W_{P_{jt}}, W_{T_{jt}}, P_{I_{jt}}$, and $P_{O_{jt}}$ as prices of permanent and temporary labor and in-house and outsourced materials, respectively.

The demand shifter and the prices that the firm faces in input markets evolve according to a Markov process that we do not further specify. As a consequence, the prices that the firm faces in period $t+1$ may depend on its productivity in period $t$ or on an average industry-wide measure of productivity. Finally, the Markov process may be time-inhomogenous to accommodate secular trends.

Bellman equation. The firm makes its decisions to maximize the expected net present value of cash flows. In contrast to its labor-augmenting productivity $\omega_{L_{jt}}$ and its Hicks-neutral productivity $\omega_{H_{jt}}$, the firm does not know the random shock $e_{jt}$ when it makes its decisions for period $t$. Letting $V_t(\cdot)$ denote the value function in period $t$, the Bellman equation for the firm’s dynamic programming problem is

$$V_t(\Omega_{jt}) = \max_{K_{jt+1}, L_{P_{jt}}, L_{T_{jt}}, Q_{M_{jt+1}}, M_{I_{jt}}, R_{jt}} P \left( X_{jt}^{-\frac{\omega}{\sigma}} \exp(\omega_{H_{jt}}), D_{jt} \right) X_{jt}^{-\frac{\omega}{\sigma}} \exp(\omega_{H_{jt}}) \mu$$

$$- C_I(K_{jt+1} - (1 - \delta)K_{jt}) - W_{P_{jt}}L_{P_{jt}} - C_{L_{jt}}(L_{P_{jt}}, L_{P_{jt-1}}) - W_{T_{jt}}L_{T_{jt}}$$

$$- (P_{I_{jt}} + P_{O_{jt}} Q_{M_{jt}}) M_{I_{jt}} - C_{Q_{M_{jt}}}(Q_{M_{jt+1}}, Q_{M_{jt}}) - C_R(R_{jt})$$

In general, the residual demand that the firm faces depends on its rivals’ prices. In taking the model to the data, one may replace rivals’ prices by an aggregate price index or dummies, although this substantially increases the dimensionality of the functions that must be nonparametrically estimated.
\[ + \frac{1}{1+\rho} E_t \left[ V_{t+1}(\Omega_{j,t+1})|\Omega_j, R_{jt} \right], \]

where

\[ X_{jt} = \beta K J_{jt} \rho + (\exp(\omega_{Ljt}) L_{jt})^{-\frac{1-\sigma}{\sigma}} + \beta M (M_{jt})^{-\frac{1-\sigma}{\sigma}}, \quad \mu = E_t \left[ \exp(e_{jt}) \right], \]

\[ \Omega_{jt} = (K_{jt}, L_{Pjt-1}, Q_{Mjt}, \omega_{Ljt}, \omega_{Hjt}, W_{Pjt}, W_{Tjt}, P_{Ijt}, P_{Ojt}, D_{jt}) \]

is the vector of state variables, and \( \rho \) is the discount rate. \( C_I(I_{jt}) \) and \( C_R(R_{jt}) \) are the cost of investment and R&D, respectively, and accommodate indivisibilities in investment and R&D projects. The firm’s dynamic programming problem gives rise to policy functions that characterize its investment and R&D decisions (and thus the values of \( K_{jt+1} \) or, equivalently, \( I_{jt} \) and \( R_{jt} \) in period \( t \)) as well as its input usage (\( L_{Pjt}, L_{Tjt}, Q_{Mjt+1} \), and \( M_{jt} \)). The labor and materials decisions are central to our empirical strategy.

**Inverse functions.** From the first-order conditions for permanent labor, temporary labor, and in-house materials we derive functions \( \tilde{h}_L(\cdot) \) and \( h_H(\cdot) \) that allow us to recover unobservable labor-augmenting and Hicks-neutral productivity from observables. Appendix C contains detailed derivations.

We make several assumptions. First, our data has hours worked by permanent and temporary workers \( L_{jt} = L_{Pjt} + L_{Tjt} \) and the (quantity) share of temporary labor \( S_{Tjt} = \frac{L_{Tjt}}{L_{jt}} \). To map \( L_{jt}^* \) in the production function in equation (6) to the data, we assume that the aggregator \( \Lambda(L_{Pjt}, L_{Tjt}) \) is linearly homogenous. This implies \( L_{jt}^* = L_{jt} \Lambda(1 - S_{Tjt}, S_{Tjt}) \).

Moreover, because our data combines the wages of permanent and temporary workers into \( W_{jt} = W_{Pjt}(1 - S_{Tjt}) + W_{Tjt} S_{Tjt} \), we assume that \( \frac{W_{Pjt}}{W_{Tjt}} = \lambda_0 \) is an (unknown) constant.\(^{12}\)

Second, our data has the materials bill \( P_{Mjt} M_{jt} = P_{Ijt} M_{Ijt} + P_{Ojt} M_{Ojt} \), the (value) share of outsourced materials \( S_{Ojt} = \frac{P_{Ojt} M_{Ojt}}{P_{Mjt} M_{jt}} \), and the price of materials \( P_{Mjt} \). To connect the model with the data, we assume \( P_{Mjt} = P_{Ijt} + P_{Ojt} Q_{Mjt} \) so that the price of materials is the effective cost of an additional unit of in-house materials. This implies \( M_{jt} = M_{Ijt} \). We further assume that \( \frac{P_{Ijt}}{P_{Ojt}} = \gamma_0 \) is an (unknown) constant and that \( \Gamma(M_{Ijt}, M_{Ojt}) \) is linearly homogenous. This implies \( M_{jt}^* = M_{jt} \Gamma \left( 1, \gamma_0 \frac{S_{Ojt}}{1-S_{Ojt}} \right) \). We finally normalize \( \Gamma(M_{Ijt}, 0) = M_{Ijt} \).

Third, the first-order condition for permanent labor involves a gap \( \Delta_{jt} \) between the wage of permanent workers \( W_{Pjt} \) and their shadow wage. We exploit the fact that we have three first-order conditions to substitute out for \( \Delta_{jt} \) in the inverse functions \( \tilde{h}_L(\cdot) \) and \( h_H(\cdot) \). As this presumes interior solutions for permanent and temporary labor, we exclude observations with \( S_{Tjt} = 0 \) and thus \( L_{Tjt} = 0 \) from the subsequent analysis.\(^{13}\)

\(^{12}\)In the Online Appendix, we use a wage regression to estimate wage premia of various types of labor. We show that the wage premia do not change much if at all over time in line with our assumption that the ratio \( \frac{W_{Pjt}}{W_{Tjt}} \) is constant.

\(^{13}\)Compare columns (1) and (2) of Tables 1 and 3 with columns (1) and (2) of Table 4 for the exact number...
Taken together, our assumptions allow us to recover (conveniently rescaled) labor-augmenting productivity \( \tilde{\omega}_{jt} \) and Hicks-neutral productivity \( \omega_{Hjt} \) as

\[
\tilde{\omega}_{jt} = \tilde{\gamma}_L + m_{jt} - l_{jt} + \sigma(p_{Mjt} - w_{jt}) - \sigma\lambda_2(S_{Tjt}) + (1 - \sigma)\gamma_1(S_{Ojt})
\]
\[
\equiv h_L(m_{jt} - l_{jt}, p_{Mjt}, w_{jt}, S_{Tjt}, S_{Ojt}),
\]
\[
\omega_{Hjt} = \gamma_H + \frac{1}{\sigma}m_{jt} + p_{Mjt} - p_{jt} - \ln \left(1 - \frac{1}{\eta(p_{jt}, D_{jt})}\right)
\]
\[
+ \left(1 + \frac{\nu\sigma}{1 - \sigma}\right)x_{jt} + \frac{1 - \sigma}{\sigma} - \gamma_1(S_{Ojt})
\]
\[
\equiv h_H(k_{jt}, m_{jt}, S_{Mjt}, p_{jt}, p_{Mjt}, D_{jt}, S_{Tjt}, S_{Ojt}),
\]

\[
(10)
\]

where \( \tilde{\gamma}_L = -\sigma \ln \beta_M \), \( \gamma_H = -\ln (\nu\beta_M \mu) \), \( \eta(p_{jt}, D_{jt}) \) is the absolute value of the price elasticity of the residual demand that the firm faces,

\[
X_{jt} = \beta_K K_{jt}^{-\frac{1 - \sigma}{\sigma}} + \beta_M (M_{jt} \exp(\gamma_1(S_{Ojt})))^{-\frac{1 - \sigma}{\sigma}} \left(1 - \frac{S_{Mjt}}{S_{Mjt}}\right) \lambda_1(S_{Tjt}) + 1
\]

and \( S_{Mjt} = \frac{P_{Mjt}M_{jt}}{VC_{jt}} \) is the share of materials in variable cost \( VC_{jt} = W_{jt}L_{jt} + P_{Mjt}M_{jt} \).

Without loss of generality, we set \( \beta_K + \beta_M = 1 \) in what follows.

We treat \( \lambda_1(S_{Tjt}), \lambda_2(S_{Tjt}), \) and \( \gamma_1(S_{Ojt}) \) as (unknown) functions of the share of temporary labor \( S_{Tjt} \), respectively, the share of outsourced materials \( S_{Ojt} \) that must be estimated nonparametrically along with the parameters of the production function. We thus think of \( \lambda_1(S_{Tjt}), \lambda_2(S_{Tjt}), \) and \( \gamma_1(S_{Ojt}) \) as “correction terms” on labor and, respectively, materials that help account for the substantial heterogeneity across the firms within an industry. Because we estimate these terms nonparametrically, they can accommodate different theories about the Spanish labor market and the role of outsourcing. For example, we develop an alternative model of outsourcing in the Online Appendix that assumes that both in-house and outsourced materials are static inputs that the firm may mix and match at will, thereby dispensing with the costly-to-adjust ratio of outsourced to in-house materials.

### 5 Empirical strategy

We combine the inverse functions in equations (10) and (11) with the laws of motion for labor-augmenting and Hicks-neutral productivity in equations (7) and (8) into estimation equations for the parameters of the production function in equation (6).

**Labor-augmenting productivity.** Substituting the inverse function in equation (10) into the law of motion in equation (7), we form our first estimation equation

\[
m_{jt} - l_{jt} = -\sigma(p_{Mjt} - w_{jt}) + \sigma\lambda_2(S_{Tjt}) - (1 - \sigma)\gamma_1(S_{Ojt})
\]

of observations and firms we exclude.
\[ +\tilde{g}_{Lt-1}(\tilde{h}_L(m_{jt-1} - l_{jt-1}, p_{Mjt-1} - w_{jt-1}, S_{Tjt-1}, S_{Ojt-1}, R_{jt-1}) + \tilde{\xi}_{Lt}, \ (12) \]

where the (conveniently rescaled) conditional expectation function is

\[ \tilde{g}_{Lt-1}(\tilde{h}_L(\cdot), R_{jt-1}) = (1 - \sigma)g_{Lt-1}\left( \frac{\tilde{h}_L(\cdot)}{1 - \sigma}, R_{jt-1} \right) \]

and \( \tilde{\xi}_{Lt} = (1 - \sigma)\xi_{Lt} \). \[14\] We allow \( \tilde{g}_{Lt-1}(\tilde{h}_L(\cdot), R_{jt-1}) \) to differ between zero and positive R&D expenditures and specify

\[ \tilde{g}_{Lt-1}(\tilde{h}_L(\cdot), R_{jt-1}) = \tilde{g}_{L0}(t - 1) + 1(R_{jt-1} = 0)\tilde{g}_{L1}(\tilde{h}_L(\cdot)) + 1(R_{jt-1} > 0)\tilde{g}_{L2}(\tilde{h}_L(\cdot), r_{jt-1}), \ (13) \]

where \( 1(\cdot) \) is the indicator function and the functions \( \tilde{g}_{L1}(\tilde{h}_L(\cdot)) \) and \( \tilde{g}_{L2}(\tilde{h}_L(\cdot), r_{jt-1}) \) are modeled as described in Appendix D. Because the Markov process governing labor-augmenting productivity is time-inhomogeneous, we allow the conditional expectation function \( \tilde{g}_{Lt-1}(\tilde{h}_L(\cdot), R_{jt-1}) \) to shift over time by \( \tilde{g}_{L0}(t - 1) \). In practice, we model this shift with time dummies.

Compared to directly estimating equation (5) by OLS, equation (12) intuitively diminishes the endogeneity problem because breaking out the part of \( \tilde{\omega}_{Lt} \) that is observable via the conditional expectation function \( \tilde{g}_{Lt-1}(\cdot) \) leaves “less” in the error term. This also facilitates instrumenting for any remaining correlation between the included variables and the error term.

In our model, labor \( l_{jt} \), materials \( m_{jt} \), the wage \( w_{jt} \), and the share of temporary labor \( S_{Tjt} \) are correlated with the productivity innovation \( \tilde{\xi}_{Lt} \) (since \( \tilde{\xi}_{Lt} \) is part of \( \tilde{\omega}_{Lt} \)). Note that \( w_{jt} = \ln (W_{Pjt}(1 - S_{Tjt}) + W_{Tjt}S_{Tjt}) \) may be correlated with \( \tilde{\xi}_{Lt} \) even though the firm takes the wage of permanent workers \( W_{Pjt} \) and the wage of temporary workers \( W_{Tjt} \) as given because \( S_{Tjt} \) may depend on \( \tilde{\omega}_{Lt} \) and \( \omega_{Hjt} \) through equations (21) and (22). We therefore base estimation on the moment conditions

\[ E\left[ A_{Lt}(z_{jt})\tilde{\xi}_{Lt} \right] = 0, \ (14) \]

where \( A_{Lt}(z_{jt}) \) is a vector of functions of the exogenous variables \( z_{jt} \) as described in Appendix D.

In considering instruments it is important to keep in mind that equation (12) models the evolution of labor-augmenting productivity \( \tilde{\omega}_{Lt} \). As a consequence, instruments have to

\[14\] Equation (12) is a semiparametric, partially linear, model with the additional restriction that the inverse function \( \tilde{h}_L(\cdot) \) is of known form. Identification in the sense of the ability to separate the parametric and nonparametric parts of the model follows from standard arguments (Robinson 1988, Newey, Powell & Vella 1999).
be uncorrelated with the productivity innovation $\tilde{\xi}_{Ljt}$ but not necessarily with productivity itself. Because $\tilde{\xi}_{Ljt}$ is the innovation to productivity $\tilde{\omega}_{Ljt}$ in period $t$, it is not known to the firm when it makes its decisions in period $t - 1$. All past decisions are therefore uncorrelated with $\tilde{\xi}_{Ljt}$. In particular, having been decided in period $t - 1$, $l_{jt-1}$ and $m_{jt-1}$ are uncorrelated with $\tilde{\xi}_{Ljt}$. In particular, having been decided in period $t - 1$, $l_{jt-1}$ and $m_{jt-1}$ are uncorrelated with $\tilde{\xi}_{Ljt}$.

In contrast to the wage $w_{jt}$, in our model the price of materials $p_{Mjt} = \ln (P_{Ijt} + P_{Ojt}Q_{Mjt})$ is uncorrelated with $\tilde{\xi}_{Ljt}$ because the ratio of outsourced to in-house materials $Q_{Mjt}$ is determined in period $t - 1$. For the same reason, the share of outsourced materials $S_{Ojt} = P_{Ojt}/(P_{Ijt} + P_{Ojt}Q_{Mjt})$ is uncorrelated with $\tilde{\xi}_{Ljt}$. We nevertheless choose to err on the side of caution and restrict ourselves to the lagged price of materials $p_{Mjt-1}$ and the lagged share of outsourcing $S_{Ojt-1}$ for instruments. Finally, time $t$ and the demand shifter $D_{jt}$ are exogenous by construction and we use them for instruments.

The reasoning that the timing of decisions and the Markovian assumption on the evolution of productivity taken together imply that all past decisions are uncorrelated with productivity innovations originates in Olley & Pakes (1996). The subsequent literature uses it to justify lagged input quantities as instruments (see, e.g., Section 2.4.1 of Ackerberg, Benkard, Berry & Pakes (2007)). In Doraszelski & Jaumandreu (2013), we extend this reasoning to justify lagged output and input prices as instruments (pp. 1347–1348). More recently, De Loecker et al. (2016) do the same to justify the lagged price of output as instrument (p. 471).

A test for overidentifying restrictions in Section 6 cannot reject the validity of the moment conditions in equation (14). More targeted tests and additional checks further suggest that there is limited reason to doubt that $w_{jt-1}$ and $p_{Mjt-1}$ are uncorrelated with $\tilde{\xi}_{Ljt}$.

**Hicks-neutral productivity.** Substituting the inverse functions in equations (10) and (11) into the production function in equation (6) and the law of motion for Hicks-neutral productivity $\omega_{Hjt}$ in equation (8), we form our second estimation equation\(^{15}\)

$$y_{jt} = -\frac{\nu}{\sigma} x_{jt}$$

\(^{15}\)There are other possible estimation equations. In particular, one can use the labor and materials decisions in equations (23) and (25) together with the production function in equation (6) to recover $\tilde{\omega}_{Ljt}$, $\omega_{Hjt}$, and $e_{jt}$ and then set up separate moment conditions in $\tilde{\xi}_{Ljt}$, $\xi_{Hjt}$, and $e_{jt}$. This may yield efficiency gains. Our estimation equation (15) has the advantage that it is similar to a CES production function that has been widely estimated in the literature.

\(^{16}\)Equation (15) is again a semiparametric model with the additional restriction that the inverse function $h_{H}(\cdot)$ is of known form.
\[ g_{Ht-1}(h_H(k_{jt-1}, m_{jt-1}, S_{Mjt-1}, p_{jt-1}, p_{Mjt-1}, D_{jt-1}, S_{Tjt-1}, S_{Ojt-1}), R_{jt-1}) + \xi_{Hjt} + e_{jt}. \]  

(15)

We specify \( g_{Ht-1}(h_H(\cdot), R_{jt-1}) \) analogously to \( \tilde{g}_{Lt-1}(\tilde{h}_L(\cdot), R_{jt-1}) \) in equation (13).

Because output \( y_{jt} \), materials \( m_{jt} \), the share of materials in variable cost \( S_{Mjt} \), and the share of temporary labor \( S_{Tjt} \) are correlated with \( \xi_{Hjt} \) in our model, we base estimation on the moment conditions

\[ E \left[ A_{Hjt}(z_{jt}) (\xi_{Hjt} + e_{jt}) \right] = 0, \]

where \( A_{Hjt}(z_{jt}) \) is a vector of function of the exogenous variables \( z_{jt} \). As before, we exploit the timing of decisions and the Markovian assumption on the evolution of productivity to rely on lags for instruments. In addition, \( k_{jt} = \ln \left( (1 - \delta) K_{jt-1} + I_{jt-1} \right) \) is determined in period \( t - 1 \) and therefore uncorrelated with \( \xi_{Hjt} \).

**Estimation.** We use the two-step GMM estimator of Hansen (1982). Let \( v_{Ljt}(\theta_L) = \tilde{\xi}_{Ljt} \) be the residual of estimation equation (12) as a function of the parameters \( \theta_L \) to be estimated and \( v_{Hjt}(\theta_H) = \xi_{Hjt} + e_{jt} \) the residual of estimation equation (15) as a function of \( \theta_H \). The GMM problem corresponding to equation (12) is

\[ \min_{\theta_L} \left[ \frac{1}{N} \sum_j A_{Lj}(z_{jt}) v_{Lj}(\theta_L) \right]^{'} \hat{W}_L \left[ \frac{1}{N} \sum_j A_{Lj}(z_{jt}) v_{Lj}(\theta_L) \right], \]

(16)

where \( A_{Lj}(z_{jt}) \) is a \( Q_L \times T_j \) matrix of functions of the exogenous variables \( z_{jt} \), \( v_{Lj}(\theta_L) \) is a \( T_j \times 1 \) vector, \( \hat{W}_L \) is a \( Q_L \times Q_L \) weighting matrix, \( Q_L \) is the number of instruments, \( T_j \) is the number of observations of firm \( j \), and \( N \) is the number of firms. We provide further details in Appendix D.

The GMM problem corresponding to equation (15) is analogous, but considerably more nonlinear. To facilitate estimation, we impose the estimated values of those parameters in \( \theta_L \) that also appear in \( \theta_H \). We correct the standard errors as described in the Online Appendix. Because they tend to be more stable, we report first-step estimates for equation (15) and use them in the subsequent analysis; however, we use second-step estimates for testing.

### 6 Labor-augmenting technological change

From equation (12) we obtain an estimate of the elasticity of substitution and recover labor-augmenting productivity at the firm level.

**Elasticity of substitution and test for overidentifying restrictions.** Tables 3 and 4 summarize different estimates of the elasticity of substitution. To compare with the
existing literature, we begin by proxying for $\tilde{\omega}_{Ljt} = (1 - \sigma)\omega_{Ljt}$ in equation \(5\) by a time trend $\tilde{\delta}_Lt$ and estimate by OLS. As can be seen from columns (3) and (4) of Table 3, with the exception of industry 9, the estimates of the elasticity of substitution are in excess of one, whereas the estimates in the previous literature lie somewhere between 0 and 1 (Chirinko 2008, Bruno 1984, Rotemberg & Woodford 1996, Oberfield & Raval 2014). This reflects, first, that a time trend is a poor proxy for labor-augmenting technological change at the firm level and, second, that the estimates are upward biased as a result of the endogeneity problem.

We address the endogeneity problem by modeling the evolution of labor-augmenting productivity and estimating equation \(12\) by GMM. To illustrate the importance of controlling for the composition of inputs in our empirical strategy, we revert to the setting in Section 2 and assume that labor $l_{jt}$ and materials $m_{jt}$ are homogenous inputs that are chosen each period to maximize short-run profits. This implies $\lambda_1(S_{Tjt}) = 1$, $\lambda_2(S_{Tjt}) = 0$, and $\gamma_1(S_{Ojt}) = 0$, so that the correction terms on labor and materials vanish and equation \(10\) reduces to equation \(5\). Columns (5)–(10) of Table 3 refer to this simplified model. As expected the estimates of the elasticity of substitution are much lower and range from 0.45 to 0.64, as can be seen from column (5). With the exception of industries 6 and 8 in which $\sigma$ is either implausibly high or low, we clearly reject the special cases of both a Leontieff ($\sigma \rightarrow 0$) and a Cobb-Douglas ($\sigma = 1$) production function.

Testing for overidentifying restrictions, however, we reject the validity of the moment conditions in the simplified model at a 5% level in five industries and we are close to rejecting in two more industries (columns (6) and (7)). To pinpoint the source of this problem, we exclude the subset of moments involving lagged materials $m_{jt-1}$ from the estimation. As can be seen from columns (8)–(10), the resulting estimates of the elasticity of substitution lie between 0.46 and 0.85 in all industries and at a 5% level we can no longer reject the validity of the moment conditions in any industry.

To see why the exogeneity of lagged materials $m_{jt-1}$ is violated contrary to the timing of decisions in our model, recall that a firm engages in outsourcing if it can procure customized parts and pieces from its suppliers that are cheaper or better than what the firm can make in house from scratch. Lumping in-house and outsourced materials together pushes these quality differences into the error term. As outsourcing often relies on contractual relationships between the firm and its suppliers, the error term is likely correlated over time and thus with lagged materials $m_{jt-1}$ as well.

Our leading specification accounts for quality differences between in-house and outsourced materials, respectively, permanent and temporary labor and differences in the use of these inputs over time and across firms. The correction term $\gamma_1(S_{Ojt})$ in equation \(12\) absorbs quality differences into the aggregator $\Gamma(M_{Ijt}, M_{Ojt})$ and accounts for the wedge that outsourcing may drive between the relative quantities and prices of materials and labor. The correction term $\lambda_2(S_{Tjt})$ similarly absorbs quality differences into the aggregator
\( \Lambda (L_{Pjt}, L_{Tjt}) \) and accounts for adjustment costs on permanent labor. As can be seen in columns (3)–(5) of Table \(4\), the correction terms duly restore the exogeneity of lagged materials \( m_{jt-1} \) as we cannot reject the validity of the moment conditions at a 5% level in any industry except for industry 7 in which we (barely) reject. Our leading estimates of \( \sigma \) in column (3) of Table \(4\) lie between 0.44 and 0.80. Compared to the estimates in column (8) of Table \(3\) there are no systematic changes and our leading estimates are somewhat lower in five industries and somewhat higher in five industries. In short, relaxing the assumption that labor and materials are homogenous and static inputs is a key step in estimating the elasticity of substitution.

**Sargan difference tests.** Because the lagged wage \( w_{jt-1} \) and the lagged price of materials \( p_{Mjt-1} \) play a key role in the estimation of equation \(12\), we supplement the omnibus test for overidentifying restrictions with two Sargan difference tests to more explicitly validate their use as instruments. In case of \( w_{jt-1} \), we compute the difference in the value of the GMM objective function when we exclude the subset of moments involving \( p_{Mjt-1} \) and when we exclude the subset of moments involving \( w_{jt-1} \) and \( p_{Mjt-1} \); in case of \( p_{Mjt-1} \) we proceed analogously. As can be seen in columns (6)–(9) of Table \(4\), the exogeneity assumption on the lagged wage is rejected at a 5% level in three industries, while that on the lagged price of materials cannot be rejected in any industry. Viewing all these tests in conjunction, to the extent that a concern about our leading specification is warranted, it appears more related to labor than to materials.

**Additional checks.** To further probe our leading specification and assess whether quality differences at a finer level play an important role, we leverage our data on the skill mix of a firm’s labor force. As we show in the Online Appendix, in our data the larger part of the variation in the wage across firms and periods can be attributed to geographic and temporal differences in the supply of labor and the fact that firms operate in different product submarkets. This part of the variation is arguably exogenous with respect to \( \tilde{\xi}_{Ljt} \). The smaller part of the variation in the wage can be attributed to differences in the skill mix and the quality of labor that may potentially be correlated with \( \tilde{\xi}_{Ljt} \).

Our estimates are robust to purging this latter variation from the lagged wage \( w_{jt-1} \). Using \( \hat{\tilde{w}}_{Qjt-1} \) to denote the part of the wage that depends on the skill mix of a firm’s labor

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17As noted in Section \(1\) we exclude observations with \( S_{Tjt} = 0 \) and thus \( L_{Tjt} = 0 \). Compare columns (1) and (2) of Tables \(1\) and \(3\) with columns (1) and (2) of Table \(4\) for the exact number of observations and firms we exclude.

18To use the same weighting matrix for both specifications and not unduly change variances when we exclude subsets of moments, we delete the appropriate rows and columns from the weighting matrix for our leading specification.

19A parallel discussion applies to materials. Kugler & Verhoogen (2012) point to differences in the quality of materials whereas Atalay (2014) documents substantial variation in the price of materials across plants in narrowly defined industries with negligible quality differences. This variation is partly due to geography and differences in cost and markup across suppliers that are arguably exogenous to a plant.
force, we replace \( w_{jt-1} \) as an instrument by \( w_{jt-1} - \hat{w}_Qjt-1 \). Compared to column (3) of Table 4, the estimates of the elasticity of substitution in column (10) decrease somewhat in three industries, remain essentially unchanged in two industries, and increase somewhat in five industries.\(^{20}\) The absence of substantial and systematic changes confirms that the variation in \( w_{jt} \) is exogenous and therefore useful in estimating equation (12), in line with the test for overidentifying restrictions.

Below we further exploit our data on the skill mix to explicitly model quality differences at a finer level by assuming that the firm faces a menu of qualities and wages in the market for permanent labor. Taken together, these additional checks alleviate concerns about the quality and composition of labor.

**Labor-augmenting technological change.** With equation (12) estimated, we recover the labor-augmenting productivity \( \omega_{Ljt} = \frac{\tilde{\omega}_{Ljt}}{1 - \sigma} \) of firm \( j \) in period \( t \) up to an additive constant from equation (10). In what follows, we therefore de-mean \( \omega_{Ljt} \) by industry. Abusing notation, we continue to use \( \omega_{Ljt} \) to denote the de-meaned labor-augmenting productivity of firm \( j \) in period \( t \).

To obtain aggregate measures representing an industry, we account for the survey design by replicating the subsample of small firms \( \frac{70\%}{5\%} = 14 \) times before pooling it with the subsample of large firms. Unless noted otherwise, we report weighed averages of individual measures, where the weight \( \mu_{jt} = \frac{P_{jt-2}Y_{jt-2}}{\sum_j P_{jt-2}Y_{jt-2}} \) is the share of sales of firm \( j \) in period \( t - 2 \). Using the second lag reduces the covariance between the weight and the variable of interest.

The growth of labor-augmenting productivity at firm \( j \) in period \( t \) is \( \Delta \omega_{Ljt} = \omega_{Ljt} - \omega_{Ljt-1} \).\(^{21}\) In line with the patterns in the data described in Section 3, our estimates imply an important role for labor-augmenting technological change. As can be seen from column (1) of Table 5, labor-augmenting productivity grows quickly, on average, with rates of growth ranging from 1.0\% and 1.7\% per year in industries 8 and 7 to 14.2\% and 18.3\% in industries 2 and 6 and above in industry 5.

Ceteris paribus \( \Delta \omega_{Ljt} \approx \frac{\exp(\omega_{Ljt})L_{jt-1}^* - \exp(\omega_{Ljt-1})L_{jt-1}^*}{\exp(\omega_{Ljt-1})L_{jt-1}^*} \) approximates the rate of growth of a firm’s effective labor force \( \exp(\omega_{Ljt-1})L_{jt-1}^* \). To facilitate comparing labor-augmenting to Hicks-neutral productivity, we approximate the rate of growth of the firm’s output \( Y_{jt-1} \) by \( \epsilon_{Ljt-2}\Delta \omega_{Ljt} \), where \( \epsilon_{Ljt-2} \) is the elasticity of output with respect to the firm’s effective

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\(^{20}\) As we show in the Online Appendix, not much changes if we isolate the part of the wage that additionally depends on firm size to try and account for the quality of labor beyond our rather coarse data on the skill mix of a firm’s labor force (Oi & Idson 1999). Compared to column (3) of Table 4, the estimates of the elasticity of substitution decrease somewhat in three industries, remain essentially unchanged in three industries, and increase somewhat in four industries.

\(^{21}\) Given the specification of \( \tilde{g}_{L,t-1}(\tilde{h}_L(\cdot), R_{jt-1}) \) in equation (13), we exclude observations where a firm switches from performing to not performing R&D or vice versa between periods \( t - 1 \) and \( t \) from the subsequent analysis. We further exclude observations where a firm switches from zero to positive outsourcing or vice versa.
labor force in period $t - 2$ (see Appendix E). This output effect, while on average close to zero in industry 9, ranges from 0.7% per year in industry 7 to 3.1%, 3.2%, and 3.6% in industries 2, 4, and 6, see column (2) of Table 5. Across industries, labor-augmenting technological change causes output to grow by 1.7% per year.

Figure 1 illustrates the magnitude of the output effect of labor-augmenting technological change and the heterogeneity in its impact across industries. The depicted index cumulates the year-to-year changes and is normalized to one in 1991. Technological change appears to have slowed in the 2000s compared to the 1990s: across industries, labor-augmenting technological change causes output to grow by 2.1% per year before 2000 and by 1.0% per year after 2000.

**Dispersion and persistence.** A substantial literature documents dispersion and persistence in productivity (see Bartelsman & Doms (2000) and Syverson (2011) and the references therein). To be able to compare labor-augmenting productivity to Hicks-neutral productivity, we focus on $\epsilon_{Ljt} - 2\omega_{Ljt}$. Because $\omega_{Ljt}$ is de-meaned, $\epsilon_{Ljt} - 2\omega_{Ljt}$ measures the

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22Because $\epsilon_{Ljt}$ depends on $\omega_{Ljt}$ as can be seen from equation (26), $\Delta \omega_{Ljt}$ is systematically negatively correlated with $\epsilon_{Ljt}$ and systematically positively correlated with $\epsilon_{Ljt-1}$. Using $\epsilon_{Ljt} - 2\omega_{Ljt}$ drastically reduces the correlation between the constituent parts of the output effect of labor-augmenting technological change.
labor-augmenting productivity of firm \( j \) in period \( t \) relative to the average productivity, suitably converted into output terms. We thus refer to \( \epsilon_{Ljt} - 2\omega_{Ljt} \) as labor-augmenting productivity in output terms in what follows.

We measure dispersion by the interquartile range of \( \epsilon_{Ljt} - 2\omega_{Ljt} \). As can be seen from column (3) of Table 5, the interquartile range is between 0.24 in industry 9 and 0.72 in industry 6. This is comparable to the existing literature. Turning from dispersion to persistence, \( \epsilon_{Ljt} - 2\omega_{Ljt} \) is highly autocorrelated (column (4)), indicating that differences in labor-augmenting productivity between firms persist over time.

**Firms’ R&D activities.** As can be seen from column (5) of Table 5, firms that perform R&D have, on average, higher levels of labor-augmenting productivity in output terms than firms that do not perform R&D in all industries. In six industries the output effect of labor-augmenting technological change for firms that perform R&D, on average, exceeds that of firms that do not perform R&D (columns (6) and (7)). Overall, our estimates indicate that firms’ R&D activities are associated not only with higher levels of labor-augmenting productivity but by and large also with higher rates of growth of labor-augmenting productivity.

**Firm turnover.** To assess the impact of firm turnover on the output effect of labor-augmenting technological change, we classify a firm as a survivor if it enters the industry in or before 1990 and does not exit in or before 2006, as an exitor if it enters the industry in or before 1990 and exits in or before 2006, and as an entrant otherwise. Survivors account for most of the output effect of labor-augmenting technological change. Their contribution is 80\% in industry 6 and above, except for industry 3 where the contribution of entrants is on par with the contribution of survivors. In the remaining industries, the contribution of entrants is small. The contribution of exitors is small in all industries.

**Skill upgrading.** In our data, there is a shift from unskilled to skilled workers. For example, the share of engineers and technicians in the labor force increases from 7.2\% in 1991 to 12.3\% in 2006. While this shift has to be seen against the backdrop of a general increase of university graduates in Spain during the 1990s and 2000s, it begs the question how much skill upgrading contributes to the growth of labor-augmenting productivity.

To answer this question—and to further alleviate concerns about the quality and composition of labor—we exploit that, in addition to the share of temporary labor \( S_{Tjt} \), our data has the share of white collar workers and the shares of engineers, respectively, technicians. We assume that there are \( Q \) types of permanent labor with qualities \( 1, \theta_2, \ldots, \theta_Q \) and corresponding wages \( W_{P1jt}, W_{P2jt}, \ldots, W_{PQjt} \). The firm, facing this menu of qualities and 

\(^{23}\) For U.S. manufacturing industries, Syverson (2004) reports an interquartile range of log labor productivity of 0.66.
wages, behaves as a price-taker in the labor market. In recognition of their different qualities, 
\[ L^*_Pjt = L^*_Pjt \left( 1 - \sum_{q=2}^{Q} \theta_q - 1 \right) S_{Pqjt} \] is an aggregate of the \( Q \) types of permanent labor, with \( L_{Pqjt} \) being the quantity of permanent labor of type \( q \) at firm \( j \) in period \( t \) and \( S_{Pqjt} \) the corresponding share in \( L^*_Pjt = \sum_{q=1}^{Q} L_{Pqjt} \). \( L^*_jt = \Lambda(L^*_Pjt, L^*_Tjt) \) is the aggregate of permanent labor \( L^*_Pjt \) (instead of \( L_{Pjt} \)) and temporary labor \( L^*_Tjt \) in the production function in equation (6). Permanent labor is subject to convex adjustment costs \( C_{BP}(B^*_Pjt, B^*_Pjt - 1) \), where \( B^*_Pjt = \sum_{q=1}^{Q} W_{Pqjt} L_{Pqjt} \) is the wage bill for permanent labor. The state vector \( \Omega_{jt} \) in the firm’s dynamic programming problem therefore includes \( B^*_Pjt - 1, W_{P1jt}, W_{P2jt}, \ldots, W_{PQjt} \) instead of \( L_{Pjt} - 1 \) and \( W_{Pjt} \).

In the Online Appendix we show that our first estimation equation (12) remains unchanged except that \( \lambda_2(S_{Tjt}) \) is replaced by \( \lambda_2(S_{Tjt}, \Theta_{jt}) \), where \( \Theta_{jt} = 1 + \sum_{q=2}^{Q} \left( \frac{W_{Pqjt}}{W_{P1jt}} - 1 \right) S_{Pqjt} \) is a quality index. We use a wage regression to estimate the wage premium \( \left( \frac{W_{Pqjt}}{W_{P1jt}} - 1 \right) \) of permanent labor of type \( q \) over type 1 and construct the quality index \( \Theta_{jt} \).

The estimates of the elasticity of substitution in column (8) of Table 5 continue to hover around 0.6 across industries, with the exception of industries 4 and 8 in which they are implausibly low. Compared to column (3) of Table 4 they decrease somewhat in three industries, remain essentially unchanged in two industries, and increase somewhat in five industries. This further supports the notion that quality differences at a finer level than permanent and temporary labor are of secondary importance for estimating equation (12).

We develop the quality index \( \Theta_{jt} \) mainly to “chip away” at the productivity residual by improving the measurement of inputs in the spirit of the productivity literature (Griliches 1964, Griliches & Jorgenson 1967). As can be seen from column (11) of Table 5, skill upgrading indeed explains some, but by no means all of the growth of labor-augmenting productivity. Compared to column (1), the rates of growth stay the same or go down in all industries. In industries 7, 8, 9, and 10 labor-augmenting productivity is stagnant or declining after accounting for skill upgrading, indicating that improvements in the skill mix over time are responsible for most of the growth of labor-augmenting productivity. In contrast, in industries 1, 2, 3, 4, 5, and 6, labor-augmenting productivity continues to grow after accounting for skill upgrading, albeit often at a much slower rate. In these industries, labor-augmenting productivity grows also because workers with a given set of skills become more productive over time.

7 The decline of the aggregate share of labor

In many advanced economies the aggregate share of labor in income has declined in past decades. While this decline has attracted considerable attention in the academic literature (Blanchard 1997, Bentolila & Saint-Paul 2004, McAdam & Willman 2013, Karabarbounis & Neiman 2014, Oberfield & Raval 2014) and in the public discussion following Piketty (2014), its causes and consequences remain contested. We use our estimates to show that
biased technological change is the primary driver of the decline of the aggregate share of labor in the Spanish manufacturing sector over our sample period.

Let \( VC_{Ljt} = W_{jt}L_{jt} \) be the wage bill, \( VC_{jt} = W_{jt}L_{jt} + P_{Mjt}M_{jt} \) variable cost, and \( S_{Ljt} = \frac{VC_{Ljt}}{VC_{jt}} \) the share of labor in variable cost of firm \( j \) in period \( t \). Let \( VC_{Lt} = \sum_j VC_{Ljt} \) and \( VC_t = \sum_j VC_{jt} \) be the corresponding industry-wide aggregates. We focus on the aggregate share of labor in variable cost

\[
S_{Lt} = \frac{VC_{Lt}}{VC_t} = \sum_j \frac{VC_{Ljt}}{VC_{jt}} \frac{VC_{jt}}{VC_t} = \sum_j S_{Ljt} \theta_{jt},
\]

where \( \theta_{jt} = \frac{VC_{jt}}{VC_t} \) is the variable cost of firm \( j \) in period \( t \) as a fraction of aggregate variable cost. As can be seen in Figure 2, the aggregate share of labor in variable cost closely tracks the aggregate share of labor in value added in the Spanish manufacturing sector in the National Accounts over our sample period.

The year-to-year change in the aggregate share of labor in variable cost is \( S_{Lt} - S_{Lt-1} \).

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Cumulated over our sample period, the decline of the aggregate share of labor ranges from 0.01 and 0.05 in industries 9 and 4 to 0.15 and 0.19 in industries 2 and 5, as can be seen in column (1) of Table 6. To obtain insight into this decline, we build on Oberfield & Raval (2014) and decompose the year-to-year change as

\[ S_{Lt} - S_{Lt-1} = \sum_j \theta_j (S_{Ljt} - S_{Ljt-1}) + \sum_j (\theta_j - \theta_{j-1}) S_{Ljt-1}. \]

The second term captures reallocation across firms. Our model enables us to further decompose the first term. Rewriting equation (10) yields

\[ S_{Ljt} = \frac{1}{1 + \exp \left( -\gamma_L + (1 - \sigma) (p_{Mjt} - w_{jt} + \omega_{Ljt}) + \sigma \lambda_2 (S_{Tjt}) - (1 - \sigma) \gamma_1 (S_{Ojt}) \right)} \] (17)

The first term may thus be driven by a change in the price of materials \( p_{Mjt} \) relative to the price of labor \( w_{jt} \), a change in labor-augmenting productivity \( \omega_{Ljt} \), a change in the share of temporary labor \( S_{Tjt} \), and a change in the share of outsourced materials \( S_{Ojt} \). To quantify these drivers, we use a second-order approximation to \( S_{Ljt} - S_{Ljt-1} \) as described in Appendix F.

We report the decomposition of the year-to-year change, cumulated over our sample period, in columns (2)–(7) of Table 6. The small size of the residual in column (7) indicates that our second-order approximation to \( S_{Ljt} - S_{Ljt-1} \) readily accommodates nonlinearities. As can be seen in column (3), biased technological change emerges as the main force behind the decline of the aggregate share of labor. Changes in input prices in column (2) attenuate the decline. In contrast, the impact of temporary labor, outsourced materials, and reallocation across firms in the remaining columns is sometimes positive and sometimes negative and mostly small.

We use our model to compute the counterfactual evolution of the aggregate share of labor absent biased technological change by zeroing out the change in labor-augmenting productivity \( \omega_{Ljt} \) in the decomposition of the year-to-year change. As can be seen in Figure 2, absent biased technological change the aggregate share of labor remains roughly constant over our sample period. We emphasize that this counterfactual holds fixed not only reallocation across firms but also the evolution of input prices, temporary labor, and outsourced materials. This may be questionable over longer stretches of time.

Our conclusion that biased technological change is the primary driver of the decline of the aggregate share of labor echoes that of Oberfield & Raval (2014). Oberfield & Raval (2014) develop a decomposition of the change in the aggregate share of labor in value added in the U.S. manufacturing sector from 1970 to 2010. Perhaps the most important difference between their decomposition and ours is that we directly measure the bias of technological

\[ \text{We estimate } S_{Lt} - S_{Lt-1} \text{ as well as the various terms of the decomposition using firms that are in the sample in periods } t \text{ and } t - 1. \]
change at the level of the individual firm, whereas Oberfield & Raval (2014) treat it as the residual of their decomposition. Despite this difference and the different data sets used, the decompositions are complementary and both point to the overwhelming role of biased technological change in the decline of the aggregate share of labor.

8 **Hicks-neutral technological change**

From equation (12) we obtain an estimate of the elasticity of substitution and recover labor-augmenting productivity at the firm level. To recover Hicks-neutral productivity and the remaining parameters of the production function, we have to estimate equation (15).

**Distributional parameters and elasticity of scale.** Table 7 reports the distributional parameters $\beta_K$ and $\beta_M = 1 - \beta_K$ and the elasticity of scale $\nu$. Our estimates of $\beta_K$ range from 0.07 in industry 8 to 0.31 in industry 6 (column (1)). Although the estimates of the elasticity of scale are rarely significantly different from one, taken together they suggest slightly decreasing returns to scale (columns (2)). We cannot reject the validity of the moment conditions in any industry by a wide margin (columns (3) and (4)).

**Price elasticity.** Column (5) of Table 7 reports the average absolute value of the price elasticity $\eta(p_{jt-1}, D_{jt-1})$ implied by our estimates. It ranges from 1.79 in industry 9 to 6.04 and 9.11 in industries 5 and 2 and averages 3.20 across industries.

**Elasticity of substitution: Lagrange-multiplier test.** The production function in equation (6) assumes that the elasticity of substitution between capital, labor, and materials is the same. We compare our leading specification to the more general nested CES production function

$$Y_{jt} = \left[ \beta_K K_{jt}^{-(1-\tau)} + \left( \exp(\omega_{Ljt}) L_{jt}^{*\alpha-1} \right)^{\frac{1}{\alpha}} + \beta_M \left( M_{jt}^{*\alpha-1} \right)^{\frac{1}{\alpha}} \right] \frac{\sigma - (1-\tau)}{1-\sigma} \exp(\omega_{Hjt}) \exp(e_{jt}),$$

where the additional parameter $\tau$ is the elasticity of substitution between capital and labor, respectively, materials. We show in the Online Appendix that our first estimation equation (12) remains unchanged and generalize our second estimation equation (15). This allows us to conduct a Lagrange-multiplier test for $\tau = \sigma$. As can be seen in columns (6) and (7) of Table 7, we cannot reject the validity of our leading specification in any industry.

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26 In light of this wide margin, we do not further probe the validity of lagged prices as instruments.

27 For U.S. manufacturing industries, Oberfield & Raval (2014) report price elasticities in a somewhat narrower range between 2.91 and 5.22 with a roughly comparable average of 3.91 across industries.
**Hicks-neutral technological change.** With equation (15) estimated, we recover the Hicks-neutral productivity $\omega_{Hjt}$ of firm $j$ in period $t$ up to an additive constant from equation (11); in what follows, we use $\omega_{Hjt}$ to denote the de-meaned Hicks-neutral productivity. We proceed as before to obtain aggregate measures representing an industry.

The growth of Hicks-neutral productivity at firm $j$ in period $t$ is $\Delta \omega_{Hjt} = \omega_{Hjt} - \omega_{Hjt-1}$. Ceteris paribus $\Delta \omega_{Hjt} \approx \frac{X_{jt}^{\omega_{Hjt}} \exp(\omega_{Hjt}) \exp(e_{jt-1}) - X_{jt-1}^{\omega_{Hjt-1}} \exp(\omega_{Hjt-1}) \exp(e_{jt-1})}{X_{jt-1}^{\omega_{Hjt-1}} \exp(\omega_{Hjt-1}) \exp(e_{jt-1})}$ approximates the rate of growth of a firm’s output $Y_{jt-1}$ and is therefore directly comparable to the output effect of labor-augmenting technological change. As can be seen from column (1) of Table 8, Hicks-neutral productivity grows quickly in five industries, with rates of growth ranging, on average, from 1.2% per year in industry 8 to 4.4% in industry 1. It grows much more slowly or barely at all in three industries, with rates of growth below 0.5% per year. While there is considerable heterogeneity in the rate of growth of Hicks-neutral productivity across industries, Hicks-neutral technological change causes output to grow by 1.4% per year.

![Figure 3: Hicks-neutral technological change. Index normalized to one in 1991.](image)

Figure 3 illustrates the magnitude of Hicks-neutral technological change. The depicted index cumulates the year-to-year changes and is normalized to one in 1991. The heterogeneity in the impact of Hicks-neutral technological change across industries clearly exceeds

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28In industry 9, in line with column (1) of Table 8, we trim values of $\Delta \omega_H$ below −0.25 and above 0.5.
that of the output effect of labor-augmenting technological change (see again Figure 1). Once again, technological change appears to have slowed in the 2000s compared to the 1990s: across industries, Hicks-neutral technological change causes output to grow by 2.7% per year before 2000 and to shrink by 0.6% per year after 2000.

**Dispersion and persistence.** We measure dispersion by the interquartile range of $\omega_{Hjt}$. As can be seen from column (2) of Table 8, the interquartile range is between 0.37 in industry 3 and 0.98 in industry 4. Hicks-neutral productivity appears to be somewhat more disperse than labor-augmenting productivity in output terms. Once again, $\omega_{Hjt}$ is highly autocorrelated (column (3)), indicating that differences in Hicks-neutral productivity between firms persist over time.

**Firms’ R&D activities.** As can be seen from column (4) of Table 8, firms that perform R&D have, on average, higher levels of Hicks-neutral productivity than firms that do not perform R&D in six industries but lower levels of Hicks-neutral productivity in four industries. While there is practically no difference in industry 10, the rate of growth of Hicks-neutral productivity for firms that perform R&D, on average, exceeds that of firms that do not perform R&D in five industries (columns (5) and (6)). Overall, our estimates indicate that firms’ R&D activities are associated with higher levels and rates of growth of Hicks-neutral productivity, although firms’ R&D activities seem less closely tied to Hicks-neutral than to labor-augmenting productivity. This is broadly consistent with the large literature on induced innovation that argues that firms direct their R&D activities to conserve the relatively more expensive factors of production, in particular labor.\(^{30}\)

**Firm turnover.** Similar to the output effect of labor-augmenting technological change, survivors account for most of Hicks-neutral technological change. Their contribution is 61% in industry 9 and above. While the contributions of entrants and exitors are small in most industries, they are negative and more sizable in industries 2, 5, 7, 8, and 10. As a result, in these industries the rate of growth of Hicks-neutral productivity is 0.7%, 3.0%, 1.2%, 1.7%, and 1.2% amongst survivors compared to 0.5%, 2.0%, 0.1%, 1.2%, and 0.2% for all firms (see again column (1) of Table 8).

**Total technological change and its components.** As productivity is multi-dimensional, we take total technological change to be $\epsilon_{Ljt} - 2 \Delta \omega_{Ljt} + \Delta \omega_{Hjt}$. Taken together, labor-augmenting and Hicks-neutral technological change cause output to grow by, on average, between 0.7% in industry 7 and 7.2% and 7.8% in industries 4 and 6, as can be seen in

\(^{29}\)For Chinese manufacturing industries, Hsieh & Klenow (2009) report an interquartile range of log total factor productivity of 1.28.

\(^{30}\)More explicitly testing for induced innovation is difficult because we do not observe what a firm does with its R&D expenditures. One way to proceed may be to add interactions of R&D expenditures and input prices to the laws of motion in equations 7 and 8. We leave this to future research.
Across all industries, total technological change causes output to grow by 3.1% per year.

The output effect of labor-augmenting technological change \( \epsilon_{Ljt-2} \Delta \omega_{Ljt} \) and Hicks-neutral technological change \( \Delta \omega_{Hjt} \) are positively correlated in nine industries while the correlation is slightly negative in one industry (column (8)). The correlation between labor-augmenting productivity in output terms \( \epsilon_{Ljt-2} \omega_{Ljt} \) and Hicks-neutral productivity \( \omega_{Hjt} \) is positive in all industries. Overall, our estimates not only provide evidence that productivity is multi- instead of single-dimensional but also suggest that the various components of productivity are intertwined.

### 9 An aggregate productivity growth decomposition

In quantifying labor-augmenting and Hicks-neutral technological change in Sections 6 and 8, we leverage our firm-level panel data to follow individual firms over time. In this section, we complement our findings by analyzing the aggregate productivity of the Spanish manufacturing sector and its growth over our sample period. To obtain insight into the drivers of growth, we decompose aggregate productivity growth along the lines of Olley & Pakes (1996).

Aggregate productivity \( \phi_t = \sum_j \mu_{jt} \phi_{jt} \) in period \( t \) is a weighted average of the productivity of individual firms, where \( \phi_{jt} \) is a measure of the productivity of firm \( j \) in period \( t \) and \( \mu_{jt} \) is its weight. We separately examine labor-augmenting productivity in output terms \( \epsilon_{Ljt-2} \omega_{Ljt} \), Hicks-neutral productivity \( \omega_{Hjt} \), and total productivity \( \epsilon_{Ljt-2} \omega_{Ljt} + \omega_{Hjt} \).

Throughout the weight \( \mu_{jt} = (p_{jt} + y_{jt}) / \sum_j (p_{jt} + y_{jt}) \) is the share of the log of sales of firm \( j \) in period \( t \).

The growth in aggregate productivity from period \( t_1 \) to period \( t_2 \) is \( \Delta \phi = \phi_{t_2} - \phi_{t_1} \). Following Olley & Pakes (1996) and Melitz & Polanec (2015), we decompose this growth as

\[
\Delta \phi = \Delta \phi^S + \mu_{t_2} E (\phi_{t_2}^E - \phi_{t_2}^S) + \mu_{t_1} X (\phi_{t_1}^X - \phi_{t_1}^S) \\
= \Delta \phi^S + N^S \text{Cov} \left( \mu \phi, \phi \right) + \mu_{t_2} (\phi_{t_2}^E - \phi_{t_2}^S) + \mu_{t_1} (\phi_{t_1}^X - \phi_{t_1}^S),
\]

where \( S, E, \) and \( X \) indexes the group of survivors, entrants, and exitors, respectively. \( \mu_t^G = \sum_{j \in G} \mu_{jt} \) is the total weight of group \( G \) in period \( t \), \( \phi_t^G = \sum_{j \in G} \frac{\mu_{jt}}{\mu_t^G} \phi_{jt} \) is the weighted average restricted to group \( G \), \( \phi_t^G = \frac{1}{N^G} \sum_{j \in G} \phi_{jt} \) is the unweighted average restricted to group \( G \), \( N^G \) is the number of firms in group \( G \), and \( \text{Cov} \left( \mu \phi, \phi \right) \) is short for

\[
\text{Cov} \left( \mu_{jt_2}^G, \phi_{jt_2} \right) - \text{Cov} \left( \mu_{jt_1}^G, \phi_{jt_1} \right).
\]

In the first line of the decomposition, the first term captures the contribution of survivors to aggregate productivity growth, the second that of entrants, and the third that of exitors. The second line further decomposes the contribution of survivors to aggregate productivity growth into a shift in the distribution of productivity.
(first term) and a change in covariance that captures reallocation (second term).

As the decomposition pertains to the population of firms, applying it to the sample of firms in our firm-level panel data is subject to a caveat. As before we account for the survey design by replicating the subsample of small firms. We classify a firm as a survivor if it enters the industry in or before period \( t_1 \) and does not exit in or before period \( t_2 \). We further classify a firm as an entrant if it enters the industry after period \( t_1 \) and as an exitor if it exits the industry in or before period \( t_2 \). Due to attrition and the periodic addition of new firms to the sample, we observe productivity for a subset of survivors in period \( t_1 \) and for another subset of survivors in period \( t_2 \). Because we average over potentially quite different subsets of firms, especially if periods \( t_1 \) and \( t_2 \) are far apart, our estimates of the various terms in the decomposition may be noisy.

We report the change in aggregate productivity and its decomposition in Table 9 for the period 1992 to 2006 and the three subperiods 1992 to 1996, 1997 to 2001, and 2002 to 2006. The change in aggregate productivity in column (1) in Table 9 is consistent with our findings in Sections 6 and 8. Aggregate labor-augmenting productivity in output terms grew by 21.7% for the period 1992 to 2006 or about 1.6% per year. Aggregate Hicks-neutral productivity grew by 19.7% or about 1.4% per year and aggregate total productivity by 41.6% or about 3.0% per year. For the later subperiods, technological change appears to have slowed down, in particular in case of aggregate Hicks-neutral and total productivity.

We report the various terms of the decomposition in the first line of equation (18) in columns (2), (5), and (6) of Table 9 and those in the second line in columns (3), (4), (5), and (6). Turning to columns (2), (5), and (6), survivors account for most of the change in aggregate total productivity and its components, again in line with our findings in Sections 6 and 8. With the possible exception of entrants for the subperiod 1992 to 1996, the contribution of entrants and exitors appears to be limited. Honing in on survivors and further decomposing their contribution, shifts in the distribution of productivity in column (3) are substantially more important than changes on the covariance in column (4). The contribution of reallocation to the change in aggregate total productivity and its components is sometimes positive and sometimes negative and mostly small.

10 Capital-augmenting technological change

As discussed in Section 3, the evolution of the relative quantities and prices of the various factors of production provides no evidence for capital-augmenting technological change. Our leading specification therefore restricts the productivities of capital and materials to change at the same rate and in lockstep with Hicks-neutral technological change. A more general specification allows for capital-augmenting productivity \( \omega_{Kjt} \) so that the production

\[ \omega_{Kjt} \]

Survivors account for less of the change for the period 1992 to 2006 than for the three subperiods simply because the definition of survivor is more demanding if periods \( t_1 \) and \( t_2 \) are further apart.
function in equation (6) becomes

\[
Y_{jt} = \left[ \beta_K \left( \exp(\omega_{Kjt})K_{jt}\right)^{-1/\sigma} + \left(\exp(\omega_{Ljt})L_{jt}\right)^{-1/\sigma} + \beta_M \left( M_{jt}^{*}\right)^{-1/\sigma} \right]^{-\omega/\sigma} \exp(\omega_{Hjt}) \exp(e_{jt}).
\]

(19)

We explore the role of capital-augmenting technological change in our data in two ways.

First, we follow Raval (2013) and parts of the previous literature on estimating aggregate production functions (see Antràs (2004) and the references therein) and assume that capital is a static input that is chosen each period to maximize short-run profits. In analogy to equation (10), we recover (conveniently rescaled) capital-augmenting productivity \( \tilde{\omega}_{Kjt} = (1 - \sigma)\omega_{Kjt} \) as

\[
\tilde{\omega}_{Kjt} = \tilde{\gamma}_K + m_{jt} - k_{jt} + \sigma(p_{Mjt} - p_{Kjt}) + (1 - \sigma)\gamma_1(S_{Ojt})
\]

\[
\equiv \tilde{h}_K(m_{jt} - k_{jt}, p_{Mjt} - p_{Kjt}, S_{Ojt}),
\]

(20)

where \( \tilde{\gamma}_K = -\sigma \ln \left( \frac{\beta_M}{\beta_K} \right) \) and we use the user cost in our data as a rough measure of the price of capital \( p_{Kjt} \). Using our leading estimates from Section 6 \[\square]\ we recover the capital-augmenting productivity \( \omega_{Kjt} = \frac{\tilde{\omega}_{Kjt}}{1 - \sigma} \) of firm \( j \) in period \( t \) up to an additive constant; in what follows, we use \( \omega_{Kjt} \) to denote the de-meaned capital-augmenting productivity.\[32\] \Delta \omega_{Kjt} \approx \frac{\exp(\omega_{Kjt})K_{jt-1} - \exp(\omega_{Kjt-1})K_{jt-1}}{\exp(\omega_{Kjt-1})K_{jt-1}} \] in column (1) of Table \[\square]\ approximates the rate of growth of a firm’s effective capital stock \( \exp(\omega_{Kjt})K_{jt-1} \) and \( \epsilon_{Kjt-2}\Delta \omega_{Kjt} \) in column (2) the rate of growth of the firm’s output \( Y_{jt-1} \), where \( \epsilon_{Kjt-2} \) is the elasticity of output with respect to the firm’s effective capital stock (see Appendix E). As can be seen from column (1), capital-augmenting productivity grows slowly, on average, with rates of growth of 0.8% per year in industry 6, 2.2% in industry 10, and 5.6% in industry 1. The rate of growth is negative in the remaining seven industries. The growth of capital-augmenting productivity is especially underwhelming in comparison to the growth of labor-augmenting productivity (see again column (1) of Table \[\square]\). The output effect of capital-augmenting technological change in column (2) is also close to zero in all industries, although this likely reflects the fact that capital is not a static input. As the user cost excludes adjustment costs, it falls short of the shadow price of capital, and using it drives down the elasticity of output with respect to the firm’s effective capital stock.

Second, we return to the usual setting in the literature following Olley & Pakes (1996) and allow the choice of capital to have dynamic implications. We follow parts of the previous literature on estimating aggregate production functions and proxy for \( \omega_{Kjt} \) by a time trend

\[m_{jt} - k_{jt} = -\sigma(p_{Mjt} - p_{Kjt}) - (1 - \sigma)\gamma_1(S_{Ojt}) + \tilde{g}_{Kt-1}(\tilde{h}_K(m_{jt-1} - k_{jt-1}, p_{Mjt-1} - p_{Kjt-1}, S_{Ojt-1}), R_{jt-1}) + \tilde{\xi}_{Kjt}.
\]

Consistent with measurement error in \( p_{Kjt} \), the resulting estimates of \( \sigma \) are very noisy and severely biased toward zero.
Our second estimation equation (15) remains unchanged except that

\[
X_{jt} = \beta_K (\exp(\delta_K t) K_{jt})^{-\frac{1}{\sigma}} + \beta_M (M_{jt} \exp(\gamma_1 (SO_{jt})))^{-\frac{1}{\sigma}} \left( 1 - \frac{S_{Mjt}}{S_{Tjt}} \lambda_1 (S_{Tjt}) + 1 \right). 
\]

Columns (3)–(7) of Table 10 summarize the resulting estimates of \( \beta_K, \nu, \) and \( \delta_K. \) The estimates of \( \beta_K \) and \( \nu \) are very comparable to those in Table 5. Moreover, the insignificant time trend leaves little room for capital-augmenting technological change in our data.

In sum, in line with the patterns in the data described in Section 3, there is little, if any, evidence for capital-augmenting technological change in our data. Of course, our ways of exploring the role of capital-augmenting technological change are less than ideal in that they either rest on the assumption that capital is a static input or abstract from firm-level heterogeneity in capital-augmenting productivity. An important question is therefore whether our approach can be extended to treat capital-augmenting productivity on par with labor-augmenting and Hicks-neutral productivity.

Recovering a third component of productivity, at a bare minimum, requires a third decision besides labor and materials to invert. Investment is a natural candidate. In contrast to the demand for labor and materials, however, investment depends on the details of the firm’s dynamic programming problem. There are two principal difficulties. First, one has to prove that the observed demands for labor and materials along with investment are jointly invertible for unobserved capital-augmenting, labor-augmenting, and Hicks-neutral productivity. Second, the inverse functions \( \tilde{h}_K(\cdot), \tilde{h}_L(\cdot), \) and \( h_H(\cdot) \) are high-dimensional. Thus, estimating these functions nonparametrically is demanding on the data. In ongoing work, Zhang (2015) proposes combining a parametric inversion that exploits the parameter restrictions between production and input demand functions similar to our paper with a nonparametric inversion of investment similar to Olley & Pakes (1996).

11 Conclusions

Technological change can increase the productivity of capital, labor, and the other factors of production in equal terms, or it can be biased towards a specific factor. In this paper, we directly assess the bias of technological change by measuring, at the level of the individual firm, how much of technological change is labor augmenting and how much of it is Hicks neutral.

To this end, we develop a dynamic model of the firm in which productivity is multi-dimensional. At the center of the model is a CES production function that parsimoniously yet robustly relates the relative quantities of materials and labor to their relative prices and labor-augmenting productivity. To properly isolate and measure labor-augmenting productivity, we account for other factors that impact this relationship, in particular, outsourcing and adjustment costs on permanent labor.
We apply our estimator to an unbalanced panel of 2375 Spanish manufacturing firms in ten industries from 1990 to 2006. Our estimates indicate limited substitutability between the various factors of production. This calls into question whether the widely-used Cobb-Douglas production function with its unitary elasticity of substitution adequately represents firm-level production processes.

Our estimates provide clear evidence that technological change is biased. Ceteris paribus labor-augmenting technological change causes output to grow, on average, in the vicinity of 1.5% per year. While skill upgrading explains some of the growth of labor augmenting productivity, in many industries labor-augmenting productivity grows because workers with a given set of skills become more productive over time. In short, our estimates cast doubt on the assumption of Hicks-neutral technological change that underlies many of the standard techniques for measuring productivity and estimating production functions.

At the same time, however, our estimates do not validate the assumption that technological change is purely labor augmenting that plays a central role in the literature on economic growth. In addition to labor-augmenting technological change, our estimates show that Hicks-neutral technological change causes output to grow, on average, in the vicinity of 1.5% per year.

While we are primarily interested in measuring how much of technological change is labor augmenting and how much of it is Hicks neutral, we also use our estimates to illustrate the consequences of biased technological change beyond the growth of output. In particular, we show that it is the primary driver of the decline of the aggregate share of labor in the Spanish manufacturing sector over our sample period. An interesting avenue for future research is to investigate the implications of biased technological change for employment. Recent research points to biased technological change as a key driver of the diverging experiences of the continental European, U.S., and U.K. economies during the 1980s and 1990s (Blanchard 1997, Caballero & Hammour 1998, Bentolila & Saint-Paul 2004, McAdam & Willman 2013). Our estimates lend themselves to decomposing firm-level changes in employment into displacement, substitution, and output effects and to compare these effects between labor-augmenting and Hicks-neutral technological change. This may be helpful for better understanding and predicting the evolution of employment as well as for designing labor market and innovation policies in the presence of biased technological change.

Appendix A  Proof of proposition 1

Rewriting the ratio of first-order conditions yields

\[ 0 = \ln \frac{\partial H}{\partial L_{jt}} \left( \exp(\omega L_{jt} - (m_{jt} - l_{jt})), 1 \right) + \omega L_{jt} - \ln \frac{\partial H}{\partial M_{jt}} \left( \exp(\omega L_{jt} - (m_{jt} - l_{jt})), 1 \right) + p_{Mjt} - w_{jt} \]

\[ = f(m_{jt} - l_{jt}, p_{Mjt} - w_{jt}, \omega L_{jt}). \]
Differentiating the so-defined function \( f(\cdot) \) yields

\[
\frac{\partial f(m_{jt} - l_{jt}, p_{Mjt} - w_{jt}, \omega_{Ljt})}{\partial (m_{jt} - l_{jt})} = \left( -\frac{\partial^2 H(\exp(\omega_{Ljt} - (m_{jt} - l_{jt})), 1)}{\partial L_{jt}^2} \frac{\partial H(\exp(\omega_{Ljt} - (m_{jt} - l_{jt})), 1)}{\partial M_{jt}} + \frac{\partial^2 H(\exp(\omega_{Ljt} - (m_{jt} - l_{jt})), 1)}{\partial M_{jt} \partial L_{jt}} \right) \exp(\omega_{Ljt} - (m_{jt} - l_{jt}))
\]

\[
= H(\exp(\omega_{Ljt} - (m_{jt} - l_{jt})), 1) \frac{\partial^2 H(\exp(\omega_{Ljt} - (m_{jt} - l_{jt})), 1)}{\partial M_{jt} \partial L_{jt}} = \frac{1}{\sigma(\exp(\omega_{Ljt} - (m_{jt} - l_{jt}))))},
\]

where the second equality uses that \( H(\exp(\omega_{Ljt})L_{jt}, M_{jt}) \) is homogeneous of degree one and the third equality uses that the elasticity of substitution between materials and labor (Chambers 1988, equation (1.13)) for the production function in equation (1) simplifies to

\[
\sigma(\exp(\omega_{Ljt} - (m_{jt} - l_{jt})))) = \frac{\partial H(\exp(\omega_{Ljt} - (m_{jt} - l_{jt})), 1)}{\partial L_{jt}} \frac{\partial H(\exp(\omega_{Ljt} - (m_{jt} - l_{jt})), 1)}{\partial M_{jt}} \frac{\partial^2 H(\exp(\omega_{Ljt} - (m_{jt} - l_{jt})), 1)}{\partial M_{jt} \partial L_{jt}}.
\]

Similarly,

\[
\frac{\partial f(m_{jt} - l_{jt}, p_{Mjt} - w_{jt}, \omega_{Ljt})}{\partial (p_{Mjt} - w_{jt})} = 1,
\]

\[
\frac{\partial f(m_{jt} - l_{jt}, p_{Mjt} - w_{jt}, \omega_{Ljt})}{\partial \omega_{Ljt}} = \frac{1}{\sigma(\exp(\omega_{Ljt} - (m_{jt} - l_{jt}))))} + 1.
\]

By the implicit function theorem, around a point \((m^0_{jt} - l^0_{jt}, p^0_{Mjt} - w^0_{jt}, \omega^0_{Ljt})\) satisfying \( f(m^0_{jt} - l^0_{jt}, p^0_{Mjt} - w^0_{jt}, \omega^0_{Ljt}) = 0 \), there exists a continuously differentiable function \( m_{jt} - l_{jt} = g(p_{Mjt} - w_{jt}, \omega_{Ljt}) \) such that \( f(g(p_{Mjt} - w_{jt}, \omega_{Ljt}), p_{Mjt} - w_{jt}, \omega_{Ljt}) = 0 \) and

\[
\frac{\partial g(p^0_{Mjt} - w^0_{jt}, \omega^0_{Ljt})}{\partial (p_{Mjt} - w_{jt})} = -\frac{\partial f(m^0_{jt} - l^0_{jt}, p^0_{Mjt} - w^0_{jt}, \omega^0_{Ljt})}{\partial (p_{Mjt} - w_{jt})} = -\sigma(\exp(\omega^0_{Ljt} - (m^0_{jt} - l^0_{jt}))) ,
\]

\[
\frac{\partial g(p^0_{Mjt} - w^0_{jt}, \omega^0_{Ljt})}{\partial \omega_{Ljt}} = -\frac{\partial f(m^0_{jt} - l^0_{jt}, p^0_{Mjt} - w^0_{jt}, \omega^0_{Ljt})}{\partial \omega_{Ljt}} = 1 - \sigma(\exp(\omega^0_{Ljt} - (m^0_{jt} - l^0_{jt}))) .
\]

The first-order Taylor series for \( m_{jt} - l_{jt} = g(p_{Mjt} - w_{jt}, \omega_{Ljt}) \) around the point \((m^0_{jt} - l^0_{jt}, p^0_{Mjt} - w^0_{jt}, \omega^0_{Ljt})\) follows immediately.

**Appendix B  Data**

We observe firms for a maximum of 17 years between 1990 and 2006. We restrict the sample to firms with at least three years of data on all variables required for estimation. The number of firms with 3, 4, ... , 17 years of data is 313, 240, 218, 215, 207, 171, 116, 189, 130, 89, 104, 57, 72, 94, and 160, respectively. Table A1 gives the industry definitions
along with their equivalent definitions in terms of the ESEE, National Accounts, and ISIC classifications (columns (1)–(3)). Based on the National Accounts in 2000, we further report the shares of the various industries in the total value added of the manufacturing sector (column (4)).

In what follows we define the variables we use for our main analysis.

- **Investment.** Value of current investments in equipment goods (excluding buildings, land, and financial assets) deflated by the price index of investment. The price of investment is the equipment goods component of the index of industry prices computed and published by the Spanish Ministry of Industry.

- **Capital.** Capital at current replacement values $\tilde{K}_{jt}$ is computed recursively from an initial estimate and the data on current investments in equipment goods $\tilde{I}_{jt}$. We update the value of the past stock of capital by means of the price index of investment $P_{It}$ as $\tilde{K}_{jt} = (1 - \delta) \frac{P_{It}}{P_{I_{t-1}}} \tilde{K}_{j_{t-1}} + \tilde{I}_{j_{t-1}}$, where $\delta$ is an industry-specific estimate of the rate of depreciation. Capital in real terms is obtained by deflating capital at current replacement values by the price index of investment as $K_{jt} = \frac{\tilde{K}_{jt}}{P_{It}}$.

- **Labor.** Total hours worked computed as the number of workers times the average hours per worker, where the latter is computed as normal hours plus average overtime minus average working time lost at the workplace.

- **Materials.** Value of intermediate goods consumption (including raw materials, components, energy, and services) deflated by a firm-specific price index of materials.

- **Output.** Value of produced goods and services computed as sales plus the variation of inventories deflated by a firm-specific price index of output.

- **Wage.** Hourly wage cost computed as total labor cost including social security payments divided by total hours worked.

- **Price of materials.** Firm-specific price index for intermediate consumption. Firms are asked about the price changes that occurred during the year for raw materials, components, energy, and services. The price index is computed as a Paasche-type index of the responses.

- **Price of output.** Firm-specific price index for output. Firms are asked about the price changes they made during the year in up to five separate markets in which they operate. The price index is computed as a Paasche-type index of the responses.

- **Demand shifter.** Firms are asked to assess the current and future situation of the main market in which they operate. The demand shifter codes the responses as 0, 0.5, and 1 for slump, stability, and expansion, respectively.

- **Share of temporary labor.** Fraction of workers with fixed-term contracts and no or small severance pay.

- **Share of outsourcing.** Fraction of customized parts and pieces that are manufactured by other firms in the value of the firm’s intermediate goods purchases.
• **R&D expenditures.** R&D expenditures include the cost of intramural R&D activities, payments for outside R&D contracts with laboratories and research centers, and payments for imported technology in the form of patent licensing or technical assistance, with the various expenditures defined according to the OECD Oslo and Frascati manuals.

We next turn to additional variables that we use for descriptive purposes, extensions, and robustness checks.

- **User cost of capital.** Computed as $P_t(r_{jt} + \delta - CPI_t)$, where $P_t$ is the price index of investment, $r_{jt}$ is a firm-specific interest rate, $\delta$ is an industry-specific estimate of the rate of depreciation, and $CPI_t$ is the rate of inflation as measured by the consumer price index.

- **Skill mix.** Fraction of non-production employees (white collar workers), workers with an engineering degree (engineers), and workers with an intermediate degree (technicians). Available in the year a firm enters the sample and every subsequent four years; assumed to be unchanging in the interim.

- **Region.** Dummy variables corresponding to the 19 Spanish autonomous communities and cities where employment is located if it is located in a unique region and another dummy variable indicating that employment is spread over several regions.

- **Product submarket.** Dummy variables corresponding to a finer breakdown of the 10 industries into subindustries (restricted to subindustries with at least five firms, see column (5) of Table A1).

- **Technological sophistication.** Dummy variable that takes the value one if the firm uses digitally controlled machines, robots, CAD/CAM, or some combination of these procedures.

- **Identification between ownership and control.** Dummy variable that takes the value one if the owner of the firm or the family of the owner hold management positions.

- **Age.** Years elapsed since the foundation of the firm with a maximum of 40 years.

- **Firm size.** Number of workers in the year the firm enters the sample.

### Appendix C  Inverse functions

The first-order conditions for permanent and temporary labor are

\[
\nu_{jt}X_{jt}^{-(1+\frac{\sigma}{\omega})}\exp(\omega_{Hjt})\exp\left(-\frac{1-\sigma}{\sigma}\omega_{Ljt}\right)(L_{jt}^*)^{-\frac{1}{\sigma}}\frac{\partial L^{*}_{jt}}{\partial L_{jt}^*} = \frac{W_{Pjt}(1+\Delta_{jt})}{P_{jt}\left(1-\frac{1}{\eta(p_{jt}, D_{jt})}\right)} (21)
\]

\[
\nu_{jt}X_{jt}^{-(1+\frac{\sigma}{\omega})}\exp(\omega_{Hjt})\exp\left(-\frac{1-\sigma}{\sigma}\omega_{Ljt}\right)(L_{jt}^*)^{-\frac{1}{\sigma}}\frac{\partial L^{*}_{jt}}{\partial L_{Tjt}^*} = \frac{W_{Tjt}}{P_{jt}\left(1-\frac{1}{\eta(p_{jt}, D_{jt})}\right)} (22)
\]

where, by the envelope theorem, the gap between the wage of permanent workers $W_{Pjt}$ and the shadow wage is

\[
\Delta_{jt} = \frac{1}{W_{Pjt}}\left(\frac{\partial C_L}{\partial L_{Pjt}}(L_{Pjt}, L_{Pjt-1}) - \frac{1}{1+\rho}\frac{\partial V_{t+1}(\Omega_{jt+1})}{\partial L_{Pjt}}[\Omega_{jt}, R_{jt}]\right) + \frac{1}{P_{jt}}\left(1-\frac{1}{\eta(p_{jt}, D_{jt})}\right)
\]
\[
\begin{align*}
\text{where the second equality follows from dividing equations (21) and (22) and solving for } \Delta_{jt}.
\end{align*}
\]

Our assumption that \( \Lambda(L_{jt}, L_{Tjt}) \) is linearly homogenous implies \( L_{jt} = L_{jt}\Lambda(1 - S_{Tjt}, S_{Tjt})\), \( \frac{\partial L_{jt}}{\partial P_{jt}} = \Lambda_{T}(1 - S_{Tjt}, S_{Tjt})\), and \( \frac{\partial L_{jt}}{\partial S_{jt}} = \Lambda_{S}(1 - S_{Tjt}, S_{Tjt})\). Using Euler’s theorem to combine equations (21) and (22) yields

\[
\nu_{jt}X_{jt}^{-\frac{1}{\eta}} \exp(\omega_{Hjt}) \left( 1 + \frac{\Delta_{jt}}{1 + \frac{\omega_{Ljt}}{\omega_{Hjt}}} \right) LW_{jt} = \nu_{jt}X_{jt}^{-\frac{1}{\eta}} \exp(\omega_{Hjt}) \left( 1 + \frac{\omega_{Ljt}}{\omega_{Hjt}} \right) LW_{jt},
\]

where the second equality follows from dividing equations (21) and (22) and solving for \( \Delta_{jt}\).

Our assumption that \( \frac{W_{Pjt}}{W_{Tjt}} = \lambda_0 \) is an (unknown) constant implies that \( \lambda_1(S_{Tjt}) \) as an (unknown) function of \( S_{Tjt}\).

Turning from the labor to the materials decision, because the firm must maintain the ratio of outsourced to in-house materials \( Q_{Mjt}\), the first-order condition for in-house materials is

\[
\nu_{jt}X_{jt}^{-\frac{1}{\sigma}} \exp(\omega_{Hjt}) \left( M_{jt}^{*} \right)^{-\frac{1}{\sigma}} \frac{dM_{jt}^{*}}{dM_{jt}} = \frac{P_{Mjt}}{P_{jt} \left( 1 - \frac{1}{\eta(P_{jt}, D_{jt})} \right)},
\]

where \( P_{Mjt} = P_{jt} + P_{Ojt}Q_{Mjt} \) is the effective cost of an additional unit of in-house materials.

Our assumption that \( \Gamma(M_{jt}, M_{Ojt}) \) is linearly homogenous implies \( M_{jt}^{*} = M_{jt}\Gamma \left( 1, \frac{P_{jt}}{P_{Ojt}}, 1 - S_{Ojt} \right) \) and \( \frac{dM_{jt}^{*}}{dM_{jt}} = \Gamma \left( 1, \frac{P_{jt}}{P_{Ojt}}, 1 - S_{Ojt} \right) \). Rewriting equation (24) yields

\[
\nu_{jt}X_{jt}^{-\frac{1}{\sigma}} \exp(\omega_{Hjt}) \left( M_{jt}^{*} \right)^{-\frac{1}{\sigma}} \Gamma \left( 1, \frac{P_{jt}}{P_{Ojt}}, 1 - S_{Ojt} \right)^{-\frac{1}{\sigma}} = \frac{P_{Mjt}}{P_{jt} \left( 1 - \frac{1}{\eta(P_{jt}, D_{jt})} \right)},
\]

Our assumption that \( \frac{P_{jt}}{P_{Ojt}} = \gamma_0 \) is an (unknown) constant implies that \( \ln \Gamma \left( 1, \gamma_0 \frac{S_{Ojt}}{1 - S_{Ojt}} \right) = \gamma_1(S_{Ojt}) \) as an (unknown) function of \( S_{Ojt}\).

Solving equations (23) and (25) for \( \omega_{Ljt} = (1 - \sigma)\omega_{Ljt} \) and \( \omega_{Hjt} \) yields equations (10) and (11), where \( \lambda_2(S_{Tjt}) = \ln \left( \lambda_1(S_{Tjt}) \Lambda(1 - S_{Tjt}, S_{Tjt})^{\frac{1}{\sigma}} \right) \).

\[\text{Equation (25) presumes an interior solution for in-house materials; it is consistent with a corner solution for outsourced materials. Indeed, absent outsourcing equation (25) reduces to the first-order condition for in-house materials.}\]
Appendix D Estimation

Unknown functions. The functions \( \tilde{g}_{L1}(h_L(\cdot)), \tilde{g}_{L2}(h_L(\cdot), r_{jt-1}), g_{H1}(h_H(\cdot)), \) and \( g_{H2}(h_H(\cdot), r_{jt-1}) \) that are part of the conditional expectation functions \( \tilde{g}_{Lt-1}(h_L(\cdot), R_{jt-1}) \) and \( g_{Ht-1}(h_H(\cdot), R_{jt-1}) \) are unknown and must be estimated nonparametrically, as must be the absolute value of the price elasticity \( \eta(p_{jt}, D_{jt}) \) and the correction terms \( \lambda_1(S_{Tjt}), \lambda_2(S_{Tjt}), \) and \( \gamma_1(S_{Ojt}) \).

We model an unknown function \( q(v) \) of one variable \( v \) by a univariate polynomial of degree \( Q \). We model an unknown function \( q(u, v) \) of two variables \( u \) and \( v \) by a complete set of polynomials of degree \( Q \). Unless otherwise noted, we omit the constant in \( q(\cdot) \) and set \( Q = 3 \) in the remainder of this paper.

Starting with the conditional expectation functions, we specify \( \tilde{g}_{L1}(h_L(\cdot)) = q(h_L(\cdot) - \gamma_L), \tilde{g}_{L2}(h_L(\cdot), r_{jt}) = q_0 + q(h_L(\cdot) - \gamma_L, r_{jt}), g_{H1}(h_H(\cdot)) = q(h_H(\cdot) - \gamma_H), \) and \( g_{H2}(h_H(\cdot), r_{jt}) = q_0 + q(h_H(\cdot) - \gamma_H, r_{jt}) \), where \( q_0 \) is a constant and the function \( q(\cdot) \) is modeled as described above. Without loss of generality, we absorb \( \gamma_L \) and \( \gamma_H \) into the overall constants of our estimation equations.

Turning to the absolute value of the price elasticity, to impose the theoretical restriction \( \eta(p_{jt}, D_{jt}) > 1 \), we specify \( \eta(p_{jt}, D_{jt}) = 1 + \exp(\varphi(p_{jt}, D_{jt})) \), where the function \( \varphi(\cdot) \) is modeled as described above except that we suppress terms involving \( D_{jt}^2 \) and \( D_{jt}^3 \). Turning to the correction terms, we specify \( \lambda_1(S_{Tjt}) = q(\ln S_{Tjt}) \) and \( \lambda_2(S_{Tjt}) = q(\ln S_{Tjt}) \) in industries 2, 3, and 10 and \( \lambda_1(S_{Tjt}) = q(\ln(1 - S_{Tjt})) \) and \( \lambda_2(S_{Tjt}) = q(\ln(1 - S_{Tjt})) \) in the remaining industries.

Finally, we specify \( \gamma_1(S_{Ojt}) = q(S_{Ojt}) \); this ensures that \( \gamma_1(S_{Ojt}) = 0 \) if \( S_{Ojt} = 0 \) in line with the normalization \( \Gamma(M_{jt}, 0) = M_{jt} \).

Parameters and instruments. Our first estimation equation [12] has 36 parameters: constant, \( \sigma \), 15 parameters in \( \tilde{g}_{L0}(t-1) \) (time dummies), 3 parameters in \( \tilde{g}_{L1}(h_L(\cdot)) \), 10 parameters in \( \tilde{g}_{L2}(h_L(\cdot), r_{jt-1}) \), 3 parameters in \( \lambda_2(S_{Tjt}) \), and 3 parameters in \( \gamma_1(S_{Ojt}) \).

Our instrumenting strategy is adapted from Doraszelski & Jaumandreu (2013) and we refer the reader to Doraszelski & Jaumandreu (2013) and the references therein for a discussion of the use of polynomials for instruments. We use the constant, 15 time dummies, the dummy for performers \( 1(R_{jt-1} > 0) \), the demand shifter \( D_{jt} \), and a univariate polynomial in \( \ln S_{Ojt-1} + m_{jt-1} \) interacted with \( 1(S_{Ojt-1} > 0) \) (3 instruments). We further use a complete set of polynomials in \( l_{jt-1}, m_{jt-1}, \) and \( p_{Mjt-1} - w_{jt-1} \) interacted with the dummy for nonperformers \( 1(R_{jt-1} = 0) \) (19 instruments). In industries 5 and 8 we replace \( p_{Mjt-1} - w_{jt-1} \) by \( p_{Mjt-1} \) in the complete set of polynomials. Finally, we use a complete set of polynomials in \( l_{jt-1}, m_{jt-1}, \) and \( p_{Mjt-1} - w_{jt-1} \) interacted with the dummy for performers \( 1(R_{jt-1} > 0) \) (34 instruments).

This yields a total of 74 instruments and 74 – 36 = 38 degrees of freedom (see column (4) of Table 4).

After imposing the estimated values from equation [12], our second estimation equation [15] has 40 parameters: constant, \( \beta_K \), \( \nu \), 15 parameters in \( g_{H0}(t-1) \) (time dummies), 3 parameters in \( g_{H1}(h_H(\cdot)) \), 10 parameters in \( g_{H2}(h_H(\cdot), r_{jt-1}) \), 3 parameters in \( \lambda_1(S_{Tjt}) \), and 6 parameters in \( \eta(p_{jt}, D_{jt}) \).

As before, we use polynomials for instruments. We use the constant, 15 time dummies, the dummy for performers \( 1(R_{jt-1} > 0) \), the demand shifter \( D_{jt} \), a univariate polynomial in \( p_{jt-1} \) (3 instruments), a univariate polynomial in \( p_{Mjt-1} - p_{jt-1} \) (3 instruments), and a univariate polynomial in \( k_{jt} \) (3 instruments). We also use a complete set of polynomials in \( \Theta_{jt} \) and \( \Theta_{jt}^3 \).

\[ ^{34} \text{To incorporate skill upgrading, we instead specify } \lambda_1(S_{Tjt}, \Theta_{jt}) = q(\ln S_{Tjt}, \ln \Theta_{jt}) \text{ and } \lambda_2(S_{Tjt}, \Theta_{jt}) = q(\ln S_{Tjt}, \ln \Theta_{jt}) \text{ in industries 2, 3, and 10 and } \lambda_1(S_{Tjt}, \Theta_{jt}) = q(\ln(1 - S_{Tjt}), \ln \Theta_{jt}) \text{ and } \lambda_2(S_{Tjt}, \Theta_{jt}) = q(\ln(1 - S_{Tjt}), \ln \Theta_{jt}) \text{ in the remaining industries, where the function } q(\cdot) \text{ is modeled as described above except that we suppress terms involving } (\ln \Theta_{jt})^2 \text{ and } (\ln \Theta_{jt})^3. \]
$M_{jt-1} \frac{1-S_{Mjt-1}}{S_{Mjt-1}}$ and $K_{jt-1}$ interacted with the dummy for nonperformers $1(R_{jt-1} = 0)$ (9 instruments). Finally, we use a complete set of polynomials in $M_{jt-1} \frac{1-S_{Mjt-1}}{S_{Mjt-1}}$ and $K_{jt-1}$ (9 instruments) and a univariate polynomial in $r_{jt-1}$ interacted with the dummy for nonperformers $1(R_{jt-1} = 0)$ (9 instruments). This yields a total of 48 instruments and $48 - 40 = 8$ degrees of freedom in industries 1, 2, 3, 6, 7, 9, and 10 (see column (3) of Table 7). In industries 4, 5, and 8, we add a univariate polynomial in $\ln(1 - S_{Tjt-1})$ (3 instruments). We replace the univariate polynomial in $k_{jt}$ by $k_{jt}$ in industries 4 and 8 and we drop $D_{jt}$ in industry 5.

**Estimation.** From the GMM problem in equation (16) with weighting matrix $\hat{W}_L = \left[ \frac{1}{N} \sum_j A_{Lj}(z_j) A_{Lj}(z_j)' \right]^{-1}$ we first obtain a consistent estimate $\hat{\theta}_L$ of $\theta_L$. This first step is the NL2SLS estimator of Amemiya (1974). In the second step, we compute the optimal estimate with weighting matrix $\hat{W}_L = \left[ \frac{1}{N} \sum_j A_{Lj}(z_j) \nu_{Lj}(\hat{\theta}_L) \nu_{Lj}(\hat{\theta}_L)' A_{Lj}(z_j)' \right]^{-1}$. Throughout the paper, we report standard errors that are robust to heteroskedasticity and autocorrelation. We further correct standard errors as described in the Online Appendix to reflect the fact that our estimates of equation (15) are conditional on those of equation (12).

**Implementation.** Code for our estimator is available from the authors upon request along with instructions for obtaining the data. We use Gauss 14.0.9 and Optmum 3.1.7. To reduce the number of parameters to search over in the GMM problem in equation (16), we “concentrate out” the parameters that enter it linearly as described in the Online Appendix. To guard against local minima, we have extensively searched over the remaining parameters, often using preliminary estimates to narrow down the range of these parameters.

**Testing.** The value of the GMM objective function for the optimal estimator, multiplied by $N$, has a limiting $\chi^2$ distribution with $Q - P$ degrees of freedom, where $Q$ is the number of instruments and $P$ the number of parameters to be estimated. We use it as a test for overidentifying restrictions or validity of the moment conditions.

**Appendix E Output effect**

Direct calculation starting from equation (6) yields the elasticity of output with respect to a firm’s effective labor force:

$$
\epsilon_{Ljt} = \frac{\partial Y_{jt}}{\partial \exp(\omega_{Ljt})} \frac{\exp(\omega_{Ljt}) L_{jt}^*}{Y_{jt}}
$$

$$
= \frac{\nu \left( \exp(\omega_{Ljt}) L_{jt}^* \right)^{-1-\sigma}}{\beta_K K_{jt}^{-\frac{1-\sigma}{\sigma}} + \left( \exp(\omega_{Ljt}) L_{jt}^* \right)^{-1-\sigma} + \beta_M \left( M_{jt}^* \right)^{-1-\sigma}}.
$$

(26)

Using equation (10) to substitute for $\omega_{Ljt}$ and simplifying we obtain

$$
\epsilon_{Ljt} = \frac{\nu^{-1-S_{Mjt}} \lambda_1(S_{Tjt})}{\frac{\beta_K}{\beta_M} \left( \frac{K_{jt}}{M_{jt} \exp(\gamma_3(S_{Djt}))} \right)^{-1-\sigma} + \frac{1-S_{Mjt}}{S_{Mjt}} \lambda_1(S_{Tjt}) + 1}.
$$

(27)
Recall from equation (23) that \( \lambda_1(S_{jt}) = 1 + \frac{\Delta_{jt}}{1 + \frac{W_{jt}}{W_{jt}^{*} + \lambda_1(S_{jt})}} \), where \( \Delta_{jt} \) is the gap between the wage of permanent workers \( W_{jt} \) and the shadow wage. To facilitate evaluating equation (27), we abstract from adjustment costs and set \( \lambda_1(S_{jt}) = 1 \).

Direct calculation starting from equation (19) also yields the elasticity of output with respect to a firm’s effective capital stock:

\[
\epsilon_{Kjt} = \frac{\partial Y_{jt}}{\partial \exp(\omega_{Kjt})} \frac{\exp(\omega_{Kjt}) K_{jt}}{Y_{jt}} - 1 - \frac{\sigma}{\lambda_1(S_{jt})} \left( \frac{1 - S_{jt}}{S_{jt}^{*} + 1} \right),
\]

where we use equations (10) and (20) to substitute for \( \omega_{Ljt} \) and \( \omega_{Kjt} \), respectively. As with equation (27), we set \( \lambda_1(S_{jt}) = 1 \) to evaluate equation (28).

### Appendix F Second-order approximation

Let \( \Upsilon_{jt} = -\gamma_{L} + (1 - \sigma)(p_{jt} - w_{jt} + \omega_{Ljt}) + \sigma \lambda_2(S_{jt}) - (1 - \sigma)\gamma_{1}(S_{Ojt}) \) and \( \Delta \Upsilon_{jt} = \Upsilon_{jt} - \Upsilon_{jt-1} \). Using equation (17) we write

\[
S_{Ljt} - S_{Ljt-1} = -S_{Ljt}(1 - S_{Ljt-1}) \left( \exp(\Delta \Upsilon_{jt}) - 1 \right)
\approx -S_{Ljt}(1 - S_{Ljt-1}) \left( \Delta \Upsilon_{jt} + \frac{1}{2} (\Delta \Upsilon_{jt})^2 \right),
\]

where we replace \( \exp(\Delta \Upsilon_{jt}) - 1 \) by its second-order Taylor series approximation around \( \Delta \Upsilon_{jt} = 0 \). We allocate the interactions in \( (\Delta \Upsilon_{jt})^2 \) in equal parts to the variables involved.

### References


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Table 1: Descriptive statistics.

<table>
<thead>
<tr>
<th>Industry</th>
<th>Obs.(^a)</th>
<th>Firms(^a)</th>
<th>Output (s. d.)</th>
<th>Capital (s. d.)</th>
<th>Labor (s. d.)</th>
<th>Materials (s. d.)</th>
<th>Price (s. d.)</th>
<th>$M_L$ (s. d.)</th>
<th>$M_W$ (s. d.)</th>
<th>$M_K$ (s. d.)</th>
<th>$M_P$ (s. d.)</th>
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<tbody>
<tr>
<td>1. Metals and metal products</td>
<td>2365</td>
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<td>0.045</td>
<td>0.051</td>
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<td>-0.021</td>
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<td>(0.176)</td>
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<td>(0.212)</td>
<td>(0.177)</td>
<td>(0.285)</td>
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<td>(0.147)</td>
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<td>7. Food, drink and tobacco</td>
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<td>0.047</td>
<td>0.003</td>
<td>0.012</td>
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<td>0.045</td>
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<td>0.014</td>
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<td>(0.326)</td>
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\(^a\) Including $S_{Tjt} = L_{Tjt} = 0.$

\(^b\) Computed for 1991 to 2006.
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<th>Industry</th>
<th>Temp. labor Obs. Share</th>
<th>Intrafirm max-min</th>
<th>Outsourcing Obs. Share</th>
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<td>(3)  (4)</td>
<td>(5)  (6)</td>
<td>(7)  (8)</td>
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<td>1. Metal and metal products</td>
<td>1877 0.260</td>
<td>0.243 0.448</td>
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<td>(79.4) (0.221)</td>
<td>(0.197) (0.360)</td>
<td>(0.090)</td>
<td>(42.9) (0.193)</td>
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<td>2. Non-metallic minerals</td>
<td>1018 0.231</td>
<td>0.232 0.482</td>
<td>0.065</td>
<td>316 0.177</td>
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<td>(80.2) (0.207)</td>
<td>(0.183) (0.403)</td>
<td>(0.063)</td>
<td>(24.9) (0.179)</td>
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<td>3. Chemical products</td>
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<td>924 0.146</td>
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<td>(0.185) (0.427)</td>
<td>(0.038)</td>
<td>(42.6) (0.183)</td>
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<td>4. Agric. and ind. machinery</td>
<td>1069 0.189</td>
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<td>(75.8) (0.181)</td>
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<td>(0.166)</td>
<td>(57.3) (0.263)</td>
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<td>5. Electrical goods</td>
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<td>763 0.181</td>
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<td>(50.7) (0.194)</td>
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<td>6. Transport equipment</td>
<td>962 0.206</td>
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<td>(0.184) (0.415)</td>
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<td>(52.8) (0.261)</td>
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<td>8. Textile, leather and shoes</td>
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<td>(0.244) (0.402)</td>
<td>(0.086)</td>
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<td>9. Timber and furniture</td>
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<td>10. Paper and printing products</td>
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<td>(0.196) (0.346)</td>
<td>(0.065)</td>
<td>(48.0) (0.253)</td>
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* Computed as difference in logs.
Table 3: Elasticity of substitution.

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<th>Industry</th>
<th>Obs.$^a$</th>
<th>Firms$^a$</th>
<th>OLS</th>
<th>GMM incl. $m_{jt-1}$ as instr.</th>
<th>GMM excl. $m_{jt-1}$ as instr.</th>
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<td>$\sigma$ (s. e.)</td>
<td>$\delta_L$ (s. e.)</td>
<td>$\sigma$ (s. e.)</td>
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<td>1. Metals and metal products</td>
<td>2365</td>
<td>313</td>
<td>1.163 (0.104)</td>
<td>0.023 (0.007)</td>
<td>0.451 (0.096)</td>
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<td>2. Non-metallic minerals</td>
<td>1270</td>
<td>163</td>
<td>1.227 (0.119)</td>
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<td>0.643 (0.086)</td>
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<td>3. Chemical products</td>
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<td>1.132 (0.095)</td>
<td>0.016 (0.007)</td>
<td>0.481 (0.099)</td>
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<td>4. Agric. and ind. machinery</td>
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<td>178</td>
<td>1.239 (0.161)</td>
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<td>0.502 (0.114)</td>
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<tr>
<td>5. Electrical goods</td>
<td>1505</td>
<td>209</td>
<td>1.402 (0.162)</td>
<td>0.017 (0.009)</td>
<td>0.469 (0.108)</td>
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<td>6. Transport equipment</td>
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<td>161</td>
<td>1.161 (0.217)</td>
<td>0.029 (0.011)</td>
<td>1.204 (0.089)</td>
</tr>
<tr>
<td>7. Food, drink and tobacco</td>
<td>2455</td>
<td>327</td>
<td>1.421 (0.094)</td>
<td>0.015 (0.008)</td>
<td>0.614 (0.063)</td>
</tr>
<tr>
<td>8. Textile, leather and shoes</td>
<td>2368</td>
<td>335</td>
<td>1.846 (0.169)</td>
<td>0.001 (0.010)</td>
<td>0.059 (0.077)</td>
</tr>
<tr>
<td>9. Timber and furniture</td>
<td>1445</td>
<td>207</td>
<td>0.793 (0.117)</td>
<td>0.013 (0.008)</td>
<td>0.461 (0.089)</td>
</tr>
<tr>
<td>10. Paper and printing products</td>
<td>1414</td>
<td>183</td>
<td>1.120 (0.107)</td>
<td>0.026 (0.008)</td>
<td>0.609 (0.057)</td>
</tr>
</tbody>
</table>

$^a$ Including $S_{Tjt} = L_{Tjt} = 0.$
Table 4: Elasticity of substitution (cont’d).

<table>
<thead>
<tr>
<th>Industry</th>
<th>Obs.</th>
<th>Firms</th>
<th>( \sigma ) (s. e.)</th>
<th>( \chi^2 (df) )</th>
<th>( \text{p val.} )</th>
<th>( \chi^2 (df) )</th>
<th>( \text{p val.} )</th>
<th>( \sigma ) (s. e.)</th>
<th>( \chi^2 (df) )</th>
<th>( \text{p val.} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Metals and metal products</td>
<td>1759</td>
<td>278</td>
<td>0.535 (0.114)</td>
<td>48.882</td>
<td>0.111</td>
<td>40.773 (25)</td>
<td>0.024 (25)</td>
<td>34.044 (25)</td>
<td>0.107 (25)</td>
<td>0.456 (0.112)</td>
</tr>
<tr>
<td>2. Non-metallic minerals</td>
<td>959</td>
<td>146</td>
<td>0.730 (0.098)</td>
<td>46.890</td>
<td>0.153</td>
<td>36.034 (25)</td>
<td>0.071 (25)</td>
<td>35.743 (25)</td>
<td>0.076 (25)</td>
<td>0.833 (0.096)</td>
</tr>
<tr>
<td>3. Chemical products</td>
<td>1610</td>
<td>269</td>
<td>0.696 (0.102)</td>
<td>46.154</td>
<td>0.171</td>
<td>33.225 (25)</td>
<td>0.126 (25)</td>
<td>32.183 (25)</td>
<td>0.153 (25)</td>
<td>0.695 (0.072)</td>
</tr>
<tr>
<td>4. Agric. and ind. machinery</td>
<td>979</td>
<td>164</td>
<td>0.606 (0.196)</td>
<td>42.420</td>
<td>0.286</td>
<td>29.398 (25)</td>
<td>0.248 (25)</td>
<td>25.684 (25)</td>
<td>0.425 (25)</td>
<td>0.762 (0.206)</td>
</tr>
<tr>
<td>5. Electrical goods</td>
<td>1147</td>
<td>191</td>
<td>0.592 (0.123)</td>
<td>46.778</td>
<td>0.155</td>
<td>38.951 (25)</td>
<td>0.037 (25)</td>
<td>32.376 (25)</td>
<td>0.147 (25)</td>
<td>0.624 (0.125)</td>
</tr>
<tr>
<td>6. Transport equipment</td>
<td>896</td>
<td>146</td>
<td>0.798 (0.088)</td>
<td>45.741</td>
<td>0.182</td>
<td>19.053 (25)</td>
<td>0.795 (25)</td>
<td>9.901 (25)</td>
<td>0.997 (25)</td>
<td>0.602 (0.097)</td>
</tr>
<tr>
<td>7. Food, drink and tobacco</td>
<td>1963</td>
<td>306</td>
<td>0.616 (0.081)</td>
<td>53.931</td>
<td>0.045</td>
<td>53.454 (25)</td>
<td>0.001 (25)</td>
<td>28.523 (25)</td>
<td>0.284 (25)</td>
<td>0.766 (0.079)</td>
</tr>
<tr>
<td>8. Textile, leather and shoes</td>
<td>1593</td>
<td>282</td>
<td>0.440 (0.186)</td>
<td>52.496</td>
<td>0.059</td>
<td>23.355 (25)</td>
<td>0.557 (25)</td>
<td>31.763 (25)</td>
<td>0.165 (25)</td>
<td>0.462 (0.149)</td>
</tr>
<tr>
<td>9. Timber and furniture</td>
<td>1114</td>
<td>188</td>
<td>0.438 (0.093)</td>
<td>39.207</td>
<td>0.416</td>
<td>28.979 (25)</td>
<td>0.265 (25)</td>
<td>22.059 (25)</td>
<td>0.632 (25)</td>
<td>0.497 (0.094)</td>
</tr>
<tr>
<td>10. Paper and printing products</td>
<td>938</td>
<td>162</td>
<td>0.530 (0.088)</td>
<td>44.448</td>
<td>0.219</td>
<td>23.642 (25)</td>
<td>0.540 (25)</td>
<td>19.822 (25)</td>
<td>0.756 (25)</td>
<td>0.449 (0.085)</td>
</tr>
</tbody>
</table>

* Excluding \( S_{Tjt} = L_{Tjt} = 0 \).
Table 5: Labor-augmenting technological change.

<table>
<thead>
<tr>
<th>Industry</th>
<th>( \Delta \omega_L )</th>
<th>( \epsilon_{L-2\omega_L} )</th>
<th>IQR</th>
<th>AC</th>
<th>p val.</th>
<th>( \chi^2 ) (df)</th>
<th>p val.</th>
<th>( \Delta \omega_L )</th>
<th>p val.</th>
<th>( \Delta \omega_L )</th>
<th>p val.</th>
<th>( \Delta \omega_L )</th>
<th>p val.</th>
<th>( \Delta \omega_L )</th>
<th>p val.</th>
<th>( \Delta \omega_L )</th>
<th>p val.</th>
<th>( \Delta \omega_L )</th>
<th>p val.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Metals and metal products</td>
<td>0.001</td>
<td>0.021</td>
<td>0.368</td>
<td>0.707</td>
<td>0.180</td>
<td>0.024</td>
<td>0.018</td>
<td>(0.117)</td>
<td>44.868</td>
<td>(0.117)</td>
<td>44.868</td>
<td>(0.117)</td>
<td>44.868</td>
<td>(0.117)</td>
<td>44.868</td>
<td>(0.117)</td>
<td>44.868</td>
<td>(0.117)</td>
<td>44.868</td>
</tr>
<tr>
<td>Non-metallic minerals</td>
<td>0.114</td>
<td>0.031</td>
<td>0.609</td>
<td>0.858</td>
<td>0.291</td>
<td>0.022</td>
<td>0.028</td>
<td>(0.092)</td>
<td>0.737</td>
<td>(0.092)</td>
<td>0.737</td>
<td>(0.092)</td>
<td>0.737</td>
<td>(0.092)</td>
<td>0.737</td>
<td>(0.092)</td>
<td>0.737</td>
<td>(0.092)</td>
<td>0.737</td>
</tr>
<tr>
<td>Chemical products</td>
<td>0.049</td>
<td>0.014</td>
<td>0.447</td>
<td>0.893</td>
<td>0.121</td>
<td>0.018</td>
<td>-0.002</td>
<td>(0.110)</td>
<td>0.618</td>
<td>(0.110)</td>
<td>0.618</td>
<td>(0.110)</td>
<td>0.618</td>
<td>(0.110)</td>
<td>0.618</td>
<td>(0.110)</td>
<td>0.618</td>
<td>(0.110)</td>
<td>0.618</td>
</tr>
<tr>
<td>Agric. and ind. machinery</td>
<td>0.126</td>
<td>0.032</td>
<td>0.220</td>
<td>0.832</td>
<td>0.385</td>
<td>0.028</td>
<td>0.046</td>
<td>(0.172)</td>
<td>0.117</td>
<td>(0.172)</td>
<td>0.117</td>
<td>(0.172)</td>
<td>0.117</td>
<td>(0.172)</td>
<td>0.117</td>
<td>(0.172)</td>
<td>0.117</td>
<td>(0.172)</td>
<td>0.117</td>
</tr>
<tr>
<td>Electrical goods</td>
<td>0.029</td>
<td>0.014</td>
<td>0.523</td>
<td>0.855</td>
<td>0.303</td>
<td>0.022</td>
<td>0.012</td>
<td>(0.128)</td>
<td>0.488</td>
<td>(0.128)</td>
<td>0.488</td>
<td>(0.128)</td>
<td>0.488</td>
<td>(0.128)</td>
<td>0.488</td>
<td>(0.128)</td>
<td>0.488</td>
<td>(0.128)</td>
<td>0.488</td>
</tr>
<tr>
<td>Transport equipment</td>
<td>0.183</td>
<td>0.036</td>
<td>0.570</td>
<td>0.803</td>
<td>0.396</td>
<td>0.045</td>
<td>0.012</td>
<td>(0.101)</td>
<td>0.781</td>
<td>(0.101)</td>
<td>0.781</td>
<td>(0.101)</td>
<td>0.781</td>
<td>(0.101)</td>
<td>0.781</td>
<td>(0.101)</td>
<td>0.781</td>
<td>(0.101)</td>
<td>0.781</td>
</tr>
<tr>
<td>Food, drink and tobacco</td>
<td>0.018</td>
<td>0.007</td>
<td>0.455</td>
<td>0.876</td>
<td>0.064</td>
<td>0.009</td>
<td>0.006</td>
<td>(0.084)</td>
<td>0.655</td>
<td>(0.084)</td>
<td>0.655</td>
<td>(0.084)</td>
<td>0.655</td>
<td>(0.084)</td>
<td>0.655</td>
<td>(0.084)</td>
<td>0.655</td>
<td>(0.084)</td>
<td>0.655</td>
</tr>
<tr>
<td>Textile, leather and shoes</td>
<td>0.010</td>
<td>0.007</td>
<td>0.347</td>
<td>0.855</td>
<td>0.165</td>
<td>0.007</td>
<td>0.009</td>
<td>(0.168)</td>
<td>0.120</td>
<td>(0.168)</td>
<td>0.120</td>
<td>(0.168)</td>
<td>0.120</td>
<td>(0.168)</td>
<td>0.120</td>
<td>(0.168)</td>
<td>0.120</td>
<td>(0.168)</td>
<td>0.120</td>
</tr>
<tr>
<td>Timber and furniture</td>
<td>0.065</td>
<td>0.001</td>
<td>0.243</td>
<td>0.608</td>
<td>0.001</td>
<td>0.007</td>
<td>0.009</td>
<td>(0.098)</td>
<td>0.275</td>
<td>(0.098)</td>
<td>0.275</td>
<td>(0.098)</td>
<td>0.275</td>
<td>(0.098)</td>
<td>0.275</td>
<td>(0.098)</td>
<td>0.275</td>
<td>(0.098)</td>
<td>0.275</td>
</tr>
<tr>
<td>Paper and printing products</td>
<td>0.023</td>
<td>0.014</td>
<td>0.275</td>
<td>0.820</td>
<td>0.137</td>
<td>0.007</td>
<td>0.009</td>
<td>(0.082)</td>
<td>0.396</td>
<td>(0.082)</td>
<td>0.396</td>
<td>(0.082)</td>
<td>0.396</td>
<td>(0.082)</td>
<td>0.396</td>
<td>(0.082)</td>
<td>0.396</td>
<td>(0.082)</td>
<td>0.396</td>
</tr>
<tr>
<td>All industries</td>
<td>0.102</td>
<td>0.017</td>
<td></td>
<td></td>
<td></td>
<td>0.020</td>
<td>0.011</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(^a\) Without replication and weighting.

\(^b\) We trim values of \( \Delta \omega_L \), respectively. \( \epsilon_{L-2\omega_L} \) below 0.25 and above 0.5.
<table>
<thead>
<tr>
<th>Industry</th>
<th>Growth of labor share&lt;sup&gt;a&lt;/sup&gt;</th>
<th>$p_M - w$</th>
<th>$\omega_L$</th>
<th>Temp. labor</th>
<th>Outsourcing</th>
<th>Reallocation</th>
<th>Residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Metal and metal products</td>
<td>-0.107</td>
<td>0.011</td>
<td>-0.086</td>
<td>-0.034</td>
<td>0.011</td>
<td>-0.004</td>
<td>-0.004</td>
</tr>
<tr>
<td>2. Non-metallic minerals</td>
<td>-0.153</td>
<td>0.011</td>
<td>-0.125</td>
<td>-0.010</td>
<td>-0.002</td>
<td>-0.026</td>
<td>-0.002</td>
</tr>
<tr>
<td>3. Chemical products</td>
<td>-0.087</td>
<td>0.018</td>
<td>-0.143</td>
<td>0.033</td>
<td>-0.002</td>
<td>0.008</td>
<td>-0.001</td>
</tr>
<tr>
<td>4. Agric. and ind. machinery</td>
<td>-0.046</td>
<td>0.031</td>
<td>-0.064</td>
<td>-0.027</td>
<td>-0.007</td>
<td>0.016</td>
<td>0.004</td>
</tr>
<tr>
<td>5. Electrical goods</td>
<td>-0.188</td>
<td>0.031</td>
<td>-0.183</td>
<td>0.025</td>
<td>-0.017</td>
<td>-0.040</td>
<td>-0.005</td>
</tr>
<tr>
<td>6. transport equipment</td>
<td>-0.066</td>
<td>0.023</td>
<td>-0.139</td>
<td>0.047</td>
<td>0.003</td>
<td>0.003</td>
<td>-0.003</td>
</tr>
<tr>
<td>7. Food, drink and tobacco</td>
<td>-0.060</td>
<td>0.022</td>
<td>-0.100</td>
<td>-0.012</td>
<td>0.023</td>
<td>-0.001</td>
<td>0.008</td>
</tr>
<tr>
<td>8. Textile, leather and shoes</td>
<td>-0.057</td>
<td>0.016</td>
<td>-0.073</td>
<td>-0.012</td>
<td>0.006</td>
<td>0.016</td>
<td>-0.009</td>
</tr>
<tr>
<td>9. Timber and furniture</td>
<td>-0.009</td>
<td>0.056</td>
<td>-0.043</td>
<td>-0.005</td>
<td>-0.002</td>
<td>-0.018</td>
<td>0.003</td>
</tr>
<tr>
<td>10. Paper and printing products</td>
<td>-0.059</td>
<td>0.020</td>
<td>-0.102</td>
<td>0.009</td>
<td>0.001</td>
<td>0.013</td>
<td>0.000</td>
</tr>
</tbody>
</table>

<sup>a</sup> Computed for 1991 to 2006.
Table 7: Distributional parameters, elasticity of scale, and price elasticity

<table>
<thead>
<tr>
<th>Industry</th>
<th>GMM</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Lagrange-</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta_K$ (s. e.)</td>
<td>$\nu$ (s. e.)</td>
<td>$\chi^2$ (df)</td>
<td>$p$ val.</td>
<td>$\eta(p-1, D-1)^a$</td>
<td>$\chi^2(1)$</td>
<td>p val.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Metals and metal products</td>
<td>0.232 (0.073)</td>
<td>0.941 (0.029)</td>
<td>3.207 (8)</td>
<td>0.921</td>
<td>2.371</td>
<td>1.023</td>
<td>0.312</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Non-metallic minerals</td>
<td>0.225 (0.133)</td>
<td>0.911 (0.063)</td>
<td>4.528 (8)</td>
<td>0.807</td>
<td>9.114</td>
<td>0.489</td>
<td>0.485</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Chemical products</td>
<td>0.137 (0.059)</td>
<td>0.933 (0.041)</td>
<td>1.109 (8)</td>
<td>0.997</td>
<td>2.431</td>
<td>0.342</td>
<td>0.559</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Agric. and ind. machinery</td>
<td>0.138 (0.125)</td>
<td>0.806 (0.088)</td>
<td>8.251 (9)</td>
<td>0.509</td>
<td>1.802</td>
<td>1.126</td>
<td>0.289</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Electrical goods</td>
<td>0.132 (0.037)</td>
<td>0.848 (0.045)</td>
<td>2.960 (10)</td>
<td>0.982</td>
<td>6.043</td>
<td>0.902</td>
<td>0.342</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Transport equipment$^b$</td>
<td>0.307 (0.182)</td>
<td>0.923 (0.061)</td>
<td></td>
<td></td>
<td>2.163</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Food, drink and tobacco</td>
<td>0.303 (0.137)</td>
<td>0.931 (0.040)</td>
<td>2.415 (8)</td>
<td>0.966</td>
<td>2.255</td>
<td>0.295</td>
<td>0.587</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8. Textile, leather and shoes</td>
<td>0.066 (0.097)</td>
<td>0.976 (0.035)</td>
<td>1.120 (9)</td>
<td>0.999</td>
<td>2.161</td>
<td>0.357</td>
<td>0.550</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9. Timber and furniture$^b$</td>
<td>0.103 (0.107)</td>
<td>0.932 (0.066)</td>
<td></td>
<td></td>
<td>1.787</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10. Paper and printing products</td>
<td>0.233 (0.083)</td>
<td>0.939 (0.041)</td>
<td>3.846 (8)</td>
<td>0.871</td>
<td>1.902</td>
<td>1.716</td>
<td>0.190</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$^a$ We trim 5% of observations at the right tail.

$^b$ We have been unable to compute the second-step GMM estimate.
Table 8: Hicks-neutral technological change.

<table>
<thead>
<tr>
<th>Industry</th>
<th>$\Delta \omega_H$</th>
<th>$\omega_H^a$</th>
<th>$\omega_H$</th>
<th>$\Delta \omega_H$</th>
<th>$\epsilon_{L,-2\Delta \omega_L} + \Delta \omega_H$</th>
<th>$\text{corr}(\epsilon_{L,-2\Delta \omega_L}, \Delta \omega_H)^a$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td>1. Metals and metal products</td>
<td>0.044</td>
<td>0.718</td>
<td>0.736</td>
<td>0.004</td>
<td>0.046</td>
<td>0.038</td>
</tr>
<tr>
<td>2. Non-metallic minerals</td>
<td>0.005</td>
<td>0.551</td>
<td>0.685</td>
<td>0.262</td>
<td>-0.019</td>
<td>0.041</td>
</tr>
<tr>
<td>3. Chemical products</td>
<td>0.019</td>
<td>0.368</td>
<td>0.872</td>
<td>0.002</td>
<td>0.022</td>
<td>0.011</td>
</tr>
<tr>
<td>4. Agric. and ind. machinery</td>
<td>0.041</td>
<td>0.978</td>
<td>0.890</td>
<td>0.445</td>
<td>0.039</td>
<td>0.022</td>
</tr>
<tr>
<td>5. Electrical goods</td>
<td>0.020</td>
<td>0.696</td>
<td>0.844</td>
<td>0.723</td>
<td>0.009</td>
<td>0.055</td>
</tr>
<tr>
<td>6. Transport equipment</td>
<td>0.042</td>
<td>0.555</td>
<td>0.595</td>
<td>0.135</td>
<td>0.058</td>
<td>-0.031</td>
</tr>
<tr>
<td>7. Food, drink and tobacco</td>
<td>0.001</td>
<td>0.760</td>
<td>0.909</td>
<td>-0.146</td>
<td>0.007</td>
<td>0.000</td>
</tr>
<tr>
<td>8. Textile, leather and shoes</td>
<td>0.012</td>
<td>0.715</td>
<td>0.859</td>
<td>-0.199</td>
<td>-0.003</td>
<td>0.032</td>
</tr>
<tr>
<td>9. Timber and furniture</td>
<td>0.021$^b$</td>
<td>0.772</td>
<td>0.772</td>
<td>-0.098</td>
<td>0.008$^b$</td>
<td>0.035$^b$</td>
</tr>
<tr>
<td>10. Paper and printing products</td>
<td>0.002</td>
<td>0.612</td>
<td>0.879</td>
<td>-0.129</td>
<td>0.006</td>
<td>0.006</td>
</tr>
<tr>
<td>All industries</td>
<td>0.014</td>
<td></td>
<td></td>
<td></td>
<td>0.016</td>
<td>0.011</td>
</tr>
</tbody>
</table>

$^a$ Without replication and weighting.

$^b$ We trim values of $\Delta \omega_H$, respectively, $\epsilon_{L,-2\Delta \omega_L} + \Delta \omega_H$ below $-0.25$ and above $0.5$. 
### Table 9: Aggregate productivity growth decomposition.

<table>
<thead>
<tr>
<th>Period</th>
<th>Change in aggregate productivity $\Delta \phi$</th>
<th>Survivors</th>
<th>Decomposition$^a$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Total $\Delta \phi^S$</td>
<td>Shift $\Delta \phi^S$</td>
</tr>
<tr>
<td>$t_1, t_2$</td>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>1992 – 2006</td>
<td>0.217</td>
<td>0.153</td>
<td>0.133</td>
</tr>
<tr>
<td>1992 – 1996</td>
<td>0.110</td>
<td>0.092</td>
<td>0.081</td>
</tr>
<tr>
<td>1997 – 2001</td>
<td>0.063</td>
<td>0.057</td>
<td>0.057</td>
</tr>
<tr>
<td>2002 – 2006</td>
<td>0.056</td>
<td>0.051</td>
<td>0.058</td>
</tr>
</tbody>
</table>

Labor-augm. productivity in output terms $\epsilon_{L,-2}\omega_L$:

<table>
<thead>
<tr>
<th>Period</th>
<th>Change</th>
<th>Survivors</th>
<th>Decomposition$^a$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Total $\Delta \phi^S$</td>
<td>Shift $\Delta \phi^S$</td>
</tr>
<tr>
<td>1992 – 2006</td>
<td>0.197</td>
<td>0.150</td>
<td>0.151</td>
</tr>
<tr>
<td>1992 – 1996</td>
<td>0.098</td>
<td>0.062</td>
<td>0.060</td>
</tr>
<tr>
<td>1997 – 2001</td>
<td>0.051</td>
<td>0.055</td>
<td>0.055</td>
</tr>
<tr>
<td>2002 – 2006</td>
<td>-0.003</td>
<td>-0.012</td>
<td>-0.005</td>
</tr>
</tbody>
</table>

Hicks-neutral productivity $\omega_H$:

<table>
<thead>
<tr>
<th>Period</th>
<th>Change</th>
<th>Survivors</th>
<th>Decomposition$^a$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Total $\Delta \phi^S$</td>
<td>Shift $\Delta \phi^S$</td>
</tr>
<tr>
<td>1992 – 2006</td>
<td>0.416</td>
<td>0.307</td>
<td>0.283</td>
</tr>
<tr>
<td>1992 – 1996</td>
<td>0.204</td>
<td>0.163</td>
<td>0.141</td>
</tr>
<tr>
<td>1997 – 2001</td>
<td>0.095</td>
<td>0.090</td>
<td>0.087</td>
</tr>
<tr>
<td>2002 – 2006</td>
<td>0.055</td>
<td>0.040</td>
<td>0.057</td>
</tr>
</tbody>
</table>

$^a$ Columns (2), (5), and (6) correspond to first line of equation 18 and add up column (1); columns (3), (4), (5), and (6) correspond to second line of equation 18 and add up column (1).

$^b$ We trim 1% of observations at each tail of the productivity distribution separately for survivors, entrants, and exitors but pooled across the start and end year.

$^c$ Changes over subperiods do not add up because of trimming and because subperiods do not overlap. Without trimming, changes over subperiods almost add up for $\epsilon_{L,-2}\omega_L$; with overlapping subperiods (1992 to 1996, 1997 to 2001, and 2002 to 2006), changes over subperiods almost add up for $\omega_H$. 
### Table 10: Capital-augmenting technological change.

<table>
<thead>
<tr>
<th>Industry</th>
<th>$\Delta \omega_K$</th>
<th>$\epsilon_{K,-2} \Delta \omega_K$</th>
<th>$\beta_K$ (s. e.)</th>
<th>$\nu$ (s. e.)</th>
<th>$\delta_K$ (s. e.)</th>
<th>$\chi^2$ (df)</th>
<th>p val.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Metals and metal products</td>
<td>0.056</td>
<td>0.004</td>
<td>0.254 (0.129)</td>
<td>0.903 (0.055)</td>
<td>0.036 (0.061)</td>
<td>2.555 (7)</td>
<td>0.923</td>
</tr>
<tr>
<td>2. Non-metallic minerals</td>
<td>-0.010</td>
<td>0.007</td>
<td>0.236 (0.102)</td>
<td>0.906 (0.072)</td>
<td>0.010 (0.072)</td>
<td>3.979 (7)</td>
<td>0.782</td>
</tr>
<tr>
<td>3. Chemical products</td>
<td>-0.018</td>
<td>0.001</td>
<td>0.125 (0.068)</td>
<td>0.942 (0.041)</td>
<td>-0.031 (0.092)</td>
<td>0.598 (7)</td>
<td>0.999</td>
</tr>
<tr>
<td>4. Agric. and ind. machinery</td>
<td>-0.020</td>
<td>0.000</td>
<td>0.182 (0.177)</td>
<td>0.801 (0.081)</td>
<td>0.031 (0.122)</td>
<td>9.026 (8)</td>
<td>0.340</td>
</tr>
<tr>
<td>5. Electrical goods</td>
<td>-0.078</td>
<td>0.000</td>
<td>0.129 (0.041)</td>
<td>0.845 (0.054)</td>
<td>-0.004 (0.056)</td>
<td>2.493 (9)</td>
<td>0.981</td>
</tr>
<tr>
<td>6. Transport equipment$^a$</td>
<td>0.008</td>
<td>0.005</td>
<td>0.115 (0.088)</td>
<td>0.981 (0.050)</td>
<td>-0.143 (0.138)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Food, drink and tobacco</td>
<td>-0.005</td>
<td>0.002</td>
<td>0.282 (0.286)</td>
<td>0.918 (0.058)</td>
<td>-0.045 (0.204)</td>
<td>2.279 (7)</td>
<td>0.943</td>
</tr>
<tr>
<td>8. Textile, leather and shoes</td>
<td>-0.085</td>
<td>-0.002</td>
<td>0.080 (0.143)</td>
<td>0.971 (0.047)</td>
<td>0.053 (0.135)</td>
<td>2.714 (8)</td>
<td>0.951</td>
</tr>
<tr>
<td>9. Timber and furniture$^a$</td>
<td>0.035$^b$</td>
<td>0.000$^b$</td>
<td>0.088 (0.119)</td>
<td>0.924 (0.067)</td>
<td>-0.021 (0.059)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10. Paper and printing products</td>
<td>0.022</td>
<td>0.007</td>
<td>0.229 (0.089)</td>
<td>0.935 (0.033)</td>
<td>0.005 (0.045)</td>
<td>3.066 (7)</td>
<td>0.879</td>
</tr>
<tr>
<td>All industries</td>
<td>-0.038</td>
<td>0.001</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$^a$ We have been unable to compute the second-step GMM estimate.

$^b$ We trim values of $\Delta \omega_K$ below -0.5 and above 0.5.
<table>
<thead>
<tr>
<th>Industry</th>
<th>Classifications</th>
<th>Share of value added</th>
<th>Number of subindustries</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Ferrous and non-ferrous metals and metal products</td>
<td>12+13 DJ C 24+25</td>
<td>13.2</td>
<td>11</td>
</tr>
<tr>
<td>2. Non-metallic minerals</td>
<td>11 DI C 23</td>
<td>8.2</td>
<td>8</td>
</tr>
<tr>
<td>3. Chemical products</td>
<td>9+10 DG-DH C 20+21+22</td>
<td>13.9</td>
<td>7</td>
</tr>
<tr>
<td>4. Agricultural and industrial machinery</td>
<td>14 DK C 28</td>
<td>7.1</td>
<td>7</td>
</tr>
<tr>
<td>5. Electrical goods</td>
<td>15+16 DL C 26+27</td>
<td>7.5</td>
<td>13</td>
</tr>
<tr>
<td>6. Transport equipment</td>
<td>17+18 DM C 29+30</td>
<td>11.6</td>
<td>7</td>
</tr>
<tr>
<td>7. Food, drink and tobacco</td>
<td>1+2+3 DA C 10+11+12</td>
<td>14.5</td>
<td>10</td>
</tr>
<tr>
<td>8. Textile, leather and shoes</td>
<td>4+5 DB-DC C 13+14+15</td>
<td>7.6</td>
<td>11</td>
</tr>
<tr>
<td>9. Timber and furniture</td>
<td>6+19 DD-DN 38 C 16+31</td>
<td>7.0</td>
<td>6</td>
</tr>
<tr>
<td>10. Paper and printing products</td>
<td>7+8 DE C 17+18</td>
<td>8.9</td>
<td>4</td>
</tr>
<tr>
<td>All industries</td>
<td></td>
<td>99.5</td>
<td>84</td>
</tr>
</tbody>
</table>