Small Bus Econ (2013) 40:397–416
DOI 10.1007/s11187-011-9367-y

# Vertical integration and efficiency: an application to the Italian machine tool industry

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Accepted: 4 August 2011 / Published online: 22 September 2011


**Abstract** This paper analyzes the relationship between firm efficiency and vertical integration in the Italian machine tool (MT) industry. The link may really be the result of a two-way causality: the effect may run from productive efficiency to the type of vertical organization (i.e. vertical integration or outsourcing), as a self-selection mechanism, or an effect from the organizational mode to the firm's performance may (also) be at work. This relationship is empirically investigated in a novel panel dataset comprising about 500 Italian MT builders, implementing two equations and instrumental variables for the two directions of causality. The evidence clearly indicates the self-selection mechanism of the most efficient firms in vertically integrated structures, while an effect from the organizational mode to the firm's efficiency is not supported.

**Keywords** Vertical integration · Technical efficiency · Italian machine tool industry · Firm heterogeneity · Instrumental variables

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**JEL Classifications** D24 · L22 · L23 · L26 · L64

## 1 Introduction

Empirical studies on productivity and efficiency at the micro-level have found large heterogeneity across firms or plants, even within narrowly defined industries (see, e.g., Syverson 2010; Dosi et al. 2011). Differences in performance between production units have mainly been attributed to variations in management skills, human capital, innovation, types of ownership, firms' international exposure and size, together with factors which are external to the firms, like technological spillovers and the regulatory environment. Similarly, the decision about which phases of production to keep inside the firm and which to leave 'outside' (i.e., the control of vertical links of production) is another factor related to a firm's productive performance, which has been widely investigated in the economics and management literature. Several models have been proposed to explain the existence of firms with different degrees of vertical integration, referring to a variety of factors such as transaction and agency costs, market-power and firms' specific capabilities (for a comprehensive survey on the determinants of the vertical scope of the firm, see Lafontaine and Slade 2007).

From a theoretical point of view, the link between vertical integration and efficiency may really be the result of two-way causality, i.e. from productive efficiency to the type of vertical organization or vice versa. Although theoretical models have tried to explain the existence and functioning of each direction of causation, no theory contemporaneously contemplates both directions, and in the last few years, this lack has led to the flowering of a vast empirical literature, the results of which are still inconclusive.

In light of these facts, we empirically examine the link between firms' efficiency and vertical integration in a novel panel dataset comprising about 500 Italian machine tool (MT) builders, examining and assessing both directions of causation. The MT industry is a strategic sector in most industrial countries (Carlsson 1989) and gathers together all the producers of metal working machinery and component. It is a natural candidate for this analysis given that its vertical structure has taken on various configurations since the 1950s (see Rolfo 1993). At the present time, the MT industry is characterized by the coexistence of various types of organizational forms and heterogeneity in productive efficiency. Our empirical analysis is structured in two steps: first, we implement a stochastic production frontier model (SFM) to estimate firms' technical efficiency; second, we investigate the relationship between the degree of vertical integration and technical efficiency, by means of two equations for the two directions of causality.

We find that, once we have controlled for firms' unobserved heterogeneity and an important set of time-variant characteristics, inefficiency levels have a positive effect on the degree of vertical disintegration, i.e., more efficient firms choose vertically integrated structures, whereas less efficient firms choose disintegrated organizations. This result, which is robust to control for the endogeneity of inefficiency in the relationship, indicates that an *ex ante* selection mechanism is at work in the industry; conversely, no significant effect is found from the organizational mode to the firm's productive performance, in a sort of 'adaptive' mechanism.

The contribution of this work runs in two main directions: first, it sheds light on the relationship between the control of vertical links of production and firms' performance, identifying the main direction through which the effect works; second, it attempts to describe the functioning of the MT industry in Italy, which is a key sector of small and medium enterprises (SMEs) which has usually been seen as central for the country's industrialization and development after the second world war. The paper is structured as follows: Sect. 2 presents the related literature on the link between vertical integration and efficiency; Sect. 3 describes the empirical strategy; Sect. 4 illustrates data; Sect. 5 shows results; and Sect. 6 adds some robustness checks. Lastly, Sect. 7 draws some conclusions.

## 2 Vertical integration and efficiency: theory and evidence

### 2.1 Theory

In a simplified setting, in order to be produced, a final good needs two inputs: an intermediate input, and a resource/input which is available to the final good producer. The manufacturer must decide either to buy the intermediate input from an external supplier (i.e., to outsource it) or make it 'in-house', vertically integrating. The two organizational forms are alternative ways of producing, which practically appear and coexist not only among various industries but also within them.

However, the wide heterogeneity of vertical boundaries among firms in the same industry is a compelling issue: why should firms adopt different degrees of vertical integration in a 'common' environment? And is there any relationship between this choice and firms' productive performance? As noted previously, the causation between the vertical organization of production and efficiency is not a one-way phenomenon. In this respect, we can refer to different approaches which explain heterogeneity in vertical integration choices: from these approaches, alternative views on the causal relationship have been put forward.

The competitive markets approach, which predicts a self-selection mechanism by heterogeneous firms into different modes of production, has been adopted in several models at the crossroads of industrial organization and international trade. Following this approach, Elberfeld (2001) demonstrates that vertically integrated and disintegrated firms may coexist in the same industry in equilibrium: integrated firms incur higher fixed costs but save on marginal costs. In the model by Antras and Helpman (2004), which rests on a property-rights setting (Grossman and Hart 1986), vertically integrated firms face higher fixed organizational costs; different variable costs depend on decisions about outsourcing production of an intermediate input, and in which country to do so. Heterogeneity in productivity is also introduced in the model: in an industry characterized by relatively higher organizational fixed costs for vertically integrated firms, only the most efficient firms are expected to choose an integrated structure.

The alternative direction of causation, i.e. from the vertical scope of the firm to its productive performance, is analyzed by different approaches in the literature. Market-power theories usually predict a positive effect from vertical integration on firms' productive efficiency which is linked to the avoidance of double marginalization or other practices that are inefficient (Perry 1989). The strategic management literature moves instead from the fact that firms may have different capabilities of managing vertical links of production. Thus, heterogeneity in the vertical scope reflects the adaptation of firms' organizational form to their capabilities. An agent-based model proposed by Jacobides (2008) illustrates how firms with heterogeneous capabilities choose different modes of vertical organization, according to the transaction costs they face. Firms can later invest in new capabilities in order to reduce transaction costs; this evolutionary process implies that firms shift from integrated to disintegrated structures and vice versa.[1] Differences in productive performance emerge *ex post* as the result of the selective pressure of the market, and causality moves from the organizational choice to the level of productive efficiency. Other authors have focused on coordination issues which may be related to the vertical scope of the firm: on the one hand, vertically integrated organizations may benefit of greater coordination along the production chain (Kogut and Zander 1996), while on the other hand, a greater focus on 'core competences' (thorough vertical disintegration/outsourcing), may lead firms to gain in average efficiency.

Overall, theories neither say a final word on the prevailing direction of causality, nor do they predict clear-cut effects; this fact has recently generated a significant amount of empirical research.

## 2.2 Evidence

The empirical evidence of firms' efficiency as a determinant of the vertical organization choice has grown in the last few years. Tomiura (2007), analyzing a representative sample of manufacturing firms in Japan, finds that the most productive firms establish international vertical links of production (through foreign direct investments), whereas less productive firms choose outsourcing; a similar result is found by Castellani and Zanfei (2007) in a representative sample of Italian firms; Federico (2010) shows a systematic positive relationship between productivity and vertical integration (either at home or abroad) for Italian manufacturing; and Bakhtiari (2011), in an unbalanced panel of Australian manufacturing firms, shows that the least efficient firms resort to outsourcing in order to save overhead costs associated with integrated structures. All these studies assess the self-selection mechanism of the most productive firms into vertically integrated organizations, but they cannot exclude the other-way-round effect.

As regards market-power-based theories, evidence of effects of vertical integration on firms' efficiency is fragmented; however, data seem to support the fact that the efficiency gains of vertical integration outweigh anti-competitive effects (Kerkvliet 1991; Chipty 2001). Furthermore, empirical works on the effects of vertical disintegration/outsourcing on firms' productive performance has gained *momentum* in the last 10 years, mainly looking at the international side of the phenomenon. Girma and Görg (2004) use establishment-level data in the chemicals, electronics and engineering industries in the UK, finding a positive effect of outsourcing on total factor productivity in the latter industry only, while Görg et al. (2008) find evidence of positive effects from outsourcing of services on the productivity of Irish manufacturing firms which, however, only holds for exporters. Heshmati (2003) and Olsen (2006) offer two surveys of studies on the relationship between (national and international) outsourcing and efficiency, with particular reference to service outsourcing, from which, however, no clear-cut effects emerge.

Thus, empirical studies have not led to any definite picture of the link between the vertical organization of

[1] Evidence on changes in the vertical organization of production has been recently provided by Malerba et al. (2008) in the computer and semiconductor industries.

production and firms' performance. In addition, only a few studies have explicitly looked at effects stemming from both directions of causality.[2]

## 3 Empirical strategy

In order to assess the link between vertical integration and efficiency in the Italian MT industry, we structure our empirical analysis in two steps. We first implement a SFM for estimating firms' technical inefficiency; then, we examine the relationship between the degree of vertical integration and the resulting inefficiency scores, using two equations and instrumental variables to control for endogeneity. Sections 3.1 and 3.2 detail the steps of the empirical analysis.

### 3.1 First step: stochastic frontier models and unobserved heterogeneity

A simple SFM for panel data can be written, in log-linear form, as

$$y_{it} = f(\mathbf{x_{it}}, \boldsymbol{\beta}) + \epsilon_{it} = \alpha + \boldsymbol{\beta}'\mathbf{x_{it}} + \epsilon_{it}, \tag{1}$$

where $y_{it}$ denotes the output of the $i$th firm in the $t$th time period, $\mathbf{x_{it}}$ is the vector of $N$ inputs used by the producer, $\boldsymbol{\beta}$ is the vector of technology parameters, and $\epsilon_{it}$ is the composed error term, where:

$$\epsilon_{it} = v_{it} - u_{it}. \tag{2}$$

Equations 1 and 2 combine to give:

$$y_{it} = \alpha + \boldsymbol{\beta}'\mathbf{x_{it}} + v_{it} - u_{it}, \tag{3}$$

where

$$v_{it} \sim \text{i.i.d.}\, N(0, \sigma_v^2), \text{ and, } u_{it} \sim \text{i.i.d.}\, N^+\,(0, \sigma_u^2). \tag{4}$$

The composed error consists of a normally distributed component $v_{it}$, which accounts for random variations of the frontier across firms (due to factors which are not under their control) and measurement errors in $y_{it}$, and a component $u_{it}$, which accounts for the difference between the actual level of production and the maximum attainable level, i.e., technical inefficiency, which is assumed to be half-normally distributed.[3] The estimation is usually performed via maximum likelihood (ML) methods to obtain consistent and efficient estimates of vector $\boldsymbol{\beta}$ and variance parameters $\sigma_v^2$ and $\sigma_u^2$. Estimates of $\epsilon_{it}$ are directly recoverable as $\widehat{\epsilon}_{it} = y_{it} - \widehat{\alpha} - \widehat{\boldsymbol{\beta}}'\mathbf{x_{it}}$, and the estimator developed by Jondrow et al. (1982) can then be used to obtain estimates of the inefficiency scores:

$$\widehat{u}_{it} = E(u_{it}|\epsilon_{it}) = \frac{\sigma_v \sigma_u}{\sigma}\left[\frac{\phi\left(\frac{\epsilon_{it}\lambda}{\sigma}\right)}{1 - \Phi\left(\frac{\epsilon_{it}\lambda}{\sigma}\right)} - \left(\frac{\epsilon_{it}\lambda}{\sigma}\right)\right], \tag{5}$$

where $\sigma = \sqrt{\sigma_v^2 + \sigma_u^2}$, $\lambda = \sigma_u/\sigma_v$, and $\phi(\cdot)$ and $\Phi(\cdot)$ denote, respectively, the density function and the cumulative function of the standard normal distribution.

The specification contained in Eqs. 3 and 4, which has been adopted in a number of works (see, e.g., Kumbhakar 1990; Battese and Coelli 1995) does not take into account the panel nature of the data, and treats them much as a pooled set of observations. This raises an important point: when differences among observations are confined to the vector of $\mathbf{x_{it}}$, the $u_{it}$ elements in Eq. 3 are intended to capture all and only the time-variant firms' inefficiency; conversely, if there are firm-specific time-invariant effects—which may be correlated to inputs—and they are not tackled in the model, this fact would lead to biased estimates in the $\boldsymbol{\beta}$ parameters. This 'pure' heterogeneity would thus affect overall residuals $\widehat{\epsilon}_{it}$, leading to an incorrect statement of technical inefficiency (see Greene 2008, p. 173).[4]

Greene (2005) proposed two SFM which contemplate both unobserved heterogeneity and time-variant inefficiency: the 'true' fixed effects (TFE) and 'true' random effects (TRE) models. The TRE model may be written as:

$$y_{it} = \alpha + \omega_i + \boldsymbol{\beta}'\mathbf{x_{it}} + v_{it} - u_{it}, \tag{6}$$

where $\omega_i$ is the random term which is specific to each firm and assumed to be uncorrelated with inputs, and

[2] Girma and Görg (2004) investigate the effects of outsourcing on productivity and the determinants of outsourcing, but the authors do not include productivity among its determinants. Federico (2010) finds direct support for the self-selection hypothesis (from efficiency to the vertical organization mode), and no support for the other direction, but he clarifies that the data prevent him from performing stronger tests on the effects from the organizational mode to firms' efficiency.

[3] Comparative results suggest that estimates of inefficiency are robust to the assumed distribution, thus leaving the choice of the distribution more a matter of computational tractability than anything else (see Greene 2008, p. 180).

[4] This issue is much like the heterogeneity (omitted variable) bias problem in standard panel data models.

the other variables and parameters are defined as in Eqs. 3 and 4. The model has a two-part error component, $\omega_i$ which should capture the unobserved heterogeneity, and $\epsilon_{it} = v_{it} - u_{it}$, which has asymmetric distribution. However, if firm-specific effects are correlated with the vector of inputs chosen by the firm, the TRE model may be prone to the heterogeneity bias.

A useful solution for correcting the TRE model, accounting for this correlation, is to adopt the adjustment proposed by Mundlak (1978), inserting the within-group means of inputs in the main frontier function as follows (Abdulai and Tietje 2007)[5]:

$$y_{it} = \alpha + \boldsymbol{\beta}'\mathbf{x_{it}} + \boldsymbol{\delta}'\overline{\mathbf{x}}_\mathbf{i} + \overline{z}_i + v_{it} - u_{it}, \tag{7}$$

where:

$$\omega_i = \boldsymbol{\delta}'\overline{\mathbf{x}}_\mathbf{i} + \overline{z}_i, \tag{8}$$

$\overline{\mathbf{x}}_\mathbf{i} = \frac{1}{T_i}\sum_1^{T_i} \mathbf{x_{it}}$ are the within-group means of inputs and $\overline{z}_i \sim N(0, \sigma^2_{\overline{z}})$ is the orthogonal-to-inputs part of the firm-specific component $\omega_i$; the other variables and parameters are defined as in Eqs. 3 and 4.

The resulting inefficiency scores may be interpreted as in deviation from the firm's average output level (average inefficiency),[6] given that the overall residual is equal to:

$$\widehat{\epsilon}_{it} = y_{it} - \widehat{\alpha} - \widehat{\boldsymbol{\beta}}'\mathbf{x_{it}} - \widehat{\delta}'\overline{\mathbf{x}}_\mathbf{i}, \tag{9}$$

and the inefficiency scores may be estimated, following the Jondrow formula, as $\widehat{u}_{it}^{\mathrm{TREMU}} = E(u_{it}|\widehat{\epsilon}_{it})$.

In order to estimate the technical inefficiency of Italian MT builders, taking unobserved heterogeneity into account, we adopted the TREMU; however, as robustness checks, we compared estimates of the TREMU model with those of the pooled stochastic frontier (PSF) in Eq. 3, the TFE and TRE models, reporting the obtained estimates and inefficiency scores in Sect. 6.1, and presenting proper statistical tests in order to support the preferred TREMU specification. For estimating the parameters of the TREMU model via maximum simulated likelihood[7] (MSL), we adopt a translog specification with three inputs:

$$\begin{aligned} y_{it} = \alpha &+ \sum_n \beta_n \cdot (x_{nit}) + \frac{1}{2}\sum_n \sum_p \beta_{np} \cdot (x_{nit}x_{pit}) \\ &+ \sum_n \delta_n \cdot (\overline{x}_{ni}) + \frac{1}{2}\sum_n \sum_p \delta_{np} \cdot (\overline{x_{ni}x_{pi}}) \\ &+ \overline{z}_i + \tau_t + v_{it} - u_{it}, \end{aligned} \tag{10}$$

where $n, p = (capital, labor, intermediates)$; we also control for factors affecting all firms in the same way in a given year by including $(t-1)$ year dummies $\tau_t$.

### 3.2 Second step: vertical integration and efficiency

In the second step of the analysis, we use the inefficiency scores recovered in the first step (by means of TREMU), and we empirically model their relationship with the degree of vertical integration, taking both directions of causality into account. In order to test whether firms characterized by different levels of efficiency self-select into different organizational forms, we have estimated variants of the following equation:

$$\ln(\mathrm{VDIS_{it}}) = \gamma_0 + \gamma_1 \widehat{\mathrm{u}}_{\mathrm{it}}^{\mathrm{TREMU}} + \boldsymbol{\lambda}'\mathbf{Z} + \eta_\mathrm{i} + \mathrm{w_{it}}, \tag{11}$$

where $\mathrm{VDIS}_{it}$ is a measure of the degree of vertical disintegration, $\widehat{u}_{it}^{\mathrm{TREMU}}$ are the estimated inefficiency scores, $\mathbf{Z}$ is a vector of time-variant controls. $\eta_i$ is a vector of firm dummies which should capture the effect of time-invariant firms' unobserved characteristics, and $w_{it}$ is the i.i.d., normally distributed error component. The $\gamma_1$ is the most important coefficient, which captures the percentage change in the degree of vertical disintegration which is due to a 1% change in the inefficiency level, ceteris paribus.

Conversely, the vertical organization of production may influence the firm's efficiency and, in order to assess the extent of this effect, we ran variants of the following equation:

[5] In the case of a SFM, in which the composed error term is asymmetrically distributed, the heterogeneity bias may still exist, but only minimally, as the correlation between firms' effects and the explanatory variables is now taken into account in the model (Abdulai and Tietje 2007, p. 7).

[6] We cross-refer the reader to Sect. 6.1 for further details in the interpretation of the inefficiency scores from the TRE model with the Mundlak adjustment (TREMU).

[7] Greene (2005) showed that the unconditional likelihood function of the model possesses no closed-form solution, so that employing the MSL estimation, by integrating out $\omega_i$ by Monte Carlo methods, may be a solution.

$$\widehat{u}_{it}^{\text{TREMU}} = \theta_0 + \theta_1 \ln(\text{VDIS}_{\text{it}}) + \boldsymbol{\varphi}'\mathbf{Z} + \eta_{\text{i}} + \xi_{\text{it}}, \tag{12}$$

where $\widehat{u}_{it}^{\text{TREMU}}$, $\text{VDIS}_{it}, \eta_i$ and $\mathbf{Z}$ are defined as in Eq. 11, and $\xi_{it}$ is the i.i.d., normally distributed error component: of particular interest is coefficient $\theta_1$, which captures the percentage change in the inefficiency level due to a 1% change in the degree of vertical disintegration. We are aware that the estimation of Eq. 12 may have limitations, such as omitted variable bias and inconsistency with respect to the first step of the analysis.[8] For this reason, as a robustness check, we also estimated the parameters of the production frontier (in Eq. 10) and those of Eq. 12 following a one-step approach: the results of the one-step and the reasons for preferring the two-step estimation procedure are listed in Sect. 6.2.

The next section details the variables which were included in the frontier model and in Eqs. 11 and 12.

## 4 Data and descriptive analysis

This study uses an original dataset, compiled by recovering data from several sources: the list of MT producers comes from the Italian Machine Tools, Robots and Automation Manufacturers Association (UCIMU), balance sheet information are from Bureau Van Dijk's AIDA dataset and sectoral deflators for output and inputs come from the Italian National Institute of Statistics (ISTAT). The data Appendix A explains in detail how the dataset was built and cleaned.

### 4.1 Description of variables

#### *4.1.1 Variables in the frontier equation*

Output (*Y*) is measured by the amount of revenues from sales and services at the end of the year, net of inventory changes and changes to contract work in progress; labor input (*L*) is measured as the total number of employees at the end of the year; capital stock (*K*) in a given year is proxied by the nominal value of tangible fixed assets; and intermediate inputs (*M*) are measured as the sum of (i) costs of raw materials consumed and goods for resale (net of changes in inventories) plus (ii) cost of services. All monetary measures are expressed in thousands of euros and have been deflated by the proper industry-level index.[9]

We are aware that replacing the quantity or real measures of output and inputs with monetary values deflated by an industry-level index may generate the so-called omitted price bias (Katayama et al. 2009), while failing to account for firm-level deviations from industry-level prices may result in bias estimates of inefficiency. This fact may constrain the reliability of the estimated inefficiency scores, and a note of caution is warranted. However, in the SFM, we partially controlled for time-invariant firms' unobserved characteristics by introducing firms' effects. If firm-level deviations from the industry-level output and input price indexes can be considered as being time-invariant in the period under analysis (10 years), an empirical model with firms' effects would eliminate them.[10] A similar argument may be made to compare firms with different capacities of negotiating input prices, and the subsequent acceptability of the deflated measures of capital and intermediates.[11] Summing up, although we cannot exclude the possibility that inefficiency scores partially reflect firm-specific prices in the output and input markets, we coped with this problem in the econometric framework.

All inputs and the output were normalized by mean correction before including them in logs in the production frontier; first-order coefficients of the translog production function can thus be interpreted as output elasticities for the average unit considered.

[8] See Wang and Schmidt (2002) for a detailed Monte Carlo comparison between the one-step and two-step procedures in estimating effects of third variables on inefficiency.

[9] Deflators for output and intermediate inputs were built using the value of production series at 2-digit level (Ateco 2007 classification), while, given the unavailability of the investments series at the 2-digit level, the deflator for capital is common to all firms belonging to the aggregate C-D-E Ateco 2007 sectors. Deflators were built as the ratio of the monetary value at current prices, in a given year, over the corresponding value in the chained series, and the base year is 2000.

[10] For example, if differences in output prices mainly depend on the firm-level mark-up and if this may be considered as invariant, a model with firms' effects would control for the specific price.

[11] Mairesse and Jaumandreau (2005), encouragingly, also found that estimating the revenue function (using nominal output measures) or the proper production function (using real or quantity measures) makes very little difference in terms of estimated output elasticities; as the main concern of our analysis is correct estimation of inefficiency scores via overall residuals, this evidence may further reassure us about the scores obtained.

#### 4.1.2 Vertical disintegration

We build a measure of vertical disintegration VDIS as the ratio of intermediate inputs ($M$) over total costs of production for the year. For the $i$th firm in the $t$th time period, this may be written as:

$$\mathrm{VDIS}_{it} = \frac{C_{\mathrm{RM},it} + C_{\mathrm{S},it}}{C_{\mathrm{RM},it} + C_{\mathrm{S},it} + C_{\mathrm{L},it} + C_{\mathrm{K},it} + C_{\mathrm{O},it}} \qquad (13)$$

where $C_{\mathrm{RM},it}$ is the cost of raw materials consumed and goods for resale (net of changes in inventories), $C_{\mathrm{S},it}$ is the cost of services, $C_{\mathrm{L},it}$ total personnel costs, $C_{K,it}$ total depreciation, amortization and write-downs (which may be interpreted as the figurative cost of capital) and $C_{\mathrm{O},it}$ is a (negligible) residual class. This ratio is an indicator of the relative share of the factors of production acquired from other firms, over all factors of production including labor and capital.[12] This measure is related to that proposed by Adelman (1955), i.e., the ratio of value added to sales, but the main advantage of our measure with respect to the Adelman index is its lower sensitivity to differences in output prices.[13] However, caution is required. First, the VDIS measure is prone to suffering from the different input prices which may be faced by MT producers. The problem should be less severe for labor and capital prices: in fact, due to the well-known salary rigidities in the Italian labor market, the focus on a single sector and the geographical agglomeration of the Italian MT builders in a few Northern Italy regions (see the data Appendix A), it is not unreasonable to assume that $w_{it} = w_{jt}$ (common salary for the same type of worker) for all firms $i \neq j$; as for capital, it is reasonable to assume that variations in $C_{\mathrm{K},it}$ among firms mainly depend on the amount of machinery and equipment acquired.[14] Nonetheless, for a given level of vertical integration, finding a high level of the VDIS variable may be due to the fact that firms' suppliers enjoy a lot of market power in selling intermediates, and we cannot control explicitly for that. However, as it has been explained in the previous section, the employment of firms' effects in the first and second step of the empirical analysis should lessen this problem if suppliers' market power can be assumed as time-invariant in the considered period. Second, we acknowledge that the variable may capture differences in labor-intensity across firms; however, in the second step of the empirical analysis, we have included a measure of size (scale) and a measure of the average wage, which should partially control for this issue.

The VDIS measure was included in logs in the regressions performed.

#### 4.1.3 Control variables

Equations 11 and 12 also include a vector $\mathbf{Z}$ of control variables. These variables come from the theoretical literature on vertical integration and outsourcing.

Standard theory generally suggests that the decision about keeping some stages of the production process in-house or relocating them 'outside' (outsourcing) depends, all else being equal, on the possibility of saving on labor costs (Abraham and Taylor 1996). We therefore introduced a measure of the average wage for the $i$th firm in the $t$th time period, $\overline{\mathrm{WAGE}}_{it}$, as the ratio of total personnel costs over the number of employees at the end of the year. The possibility of achieving scale economies in the production of the intermediate input may also affect the decision about vertical integration; thus, we included a measure of firm size, $\mathrm{SIZE}_{it}$, defined as the total number of employees at the end of the year.[15]

[12] A value of 1 means that the firm depends on external suppliers for almost all its production inputs; values near 0 indicate that the firm bases its production on its own capital and labor, i.e., it is vertically integrated.

[13] The empirical literature on vertical integration suggests alternative measures compared with the Adelman index (Vannoni 1996). Input–output (I–O) tables were used by Davies and Morris (1995) to build a vertical integration index ($\mathrm{VI}^k$) which aims at capturing intra-firm flows of goods, the 'heart' of the vertical integration concept, but it imputes them from intra-industry flows. Our measure of vertical disintegration does not impose common-to-the-industry intra-firm flows, nor do we have the breakdown of turnover by sector, which is a fundamental requirement in order to build the $\mathrm{VI}^k$ index.

[14] In fact, the yearly quotas of depreciations and amortizations are computed by following fiscal deductibility purposes, using the coefficients established by the Ministry of Economy and Finance at sectoral level—i.e., they are common to all firms belonging to the same sector—in the Ministerial Decree 31.12.1988.

[15] The inclusion of a measure of size also allows us to control partially for other firms' characteristics which are not directly observable in our dataset, such as the R&D intensity and the internationalization *status*, which may well be correlated with both vertical integration and firms' efficiency.

The literature on transaction costs and property rights suggested other determinants of the vertical integration choice, such as the degree of asset specificity and environmental uncertainty. Unfortunately, we have no information on the degree of specificity of single inputs, and we follow Antonietti and Cainelli (2007) by including the ratio of total debts to total assets at the end of the year, $\text{ASS\_UNS}_{it}$, which should be negatively related to the average degree of specificity of all the firm's assets.[16] We also included a measure of volume uncertainty in the downstream market: following Lieberman (1991), volume uncertainty is measured as the sum of squared residuals between time $t$ and time $t - x$ of the following regression:

$$y_{it} = \psi_0 + \psi_1(t) + \psi_2(t^2) + \psi_3(t^3) + \upsilon_{it}, \tag{14}$$

where $y_{it}$ is (the log of) the output measure and $t = (1, \ldots, 10)$ is an integer increasing in each year. The measure may be defined as:

$$\text{UNCE}_{it} = \frac{1}{x+1} \sum_{t=t-x}^{t} \hat{\upsilon}_{it}^2, \tag{15}$$

where $x = 2$ for years which go from 2000 to 2007, $x = 1$ for 1999 and $x = 0$ for 1998. Lastly, because the MT industry is characterized by cycles in the aggregate demand for MTs by its customers (such as producers of automobiles, aircraft and home appliances), as suggested by Wieandt (1994, p. 427), we introduced into the regressions a dummy for the years showing a downward trend in the aggregate value of production (DCYCLE), i.e., 2002, 2003 and 2004.

All controls (except for *DCYCLE*) have been included in logs in the regressions.

### 4.2 Descriptive statistics and industry overview

The original database contains 3,875 observations (corresponding to 505 firms) with information on output and inputs for the period 1998–2007, which were used to estimate the parameters of the frontier model and recover the inefficiency scores. It also contains 2,973 observations (401 firms) with full information on all relevant variables for the same period; this smaller sample was used for estimating Eqs. 11 and 12. The data Appendix A explains how samples were obtained.

The figures from Table 1 are in line with general statistics on the industry appearing in technical reports (see UCIMU 2007). The vast majority of producers of MTs are SMEs, in which almost 75% of producers invoices less than 13 million euros, and the top 10% invoices (at least) twice that amount. The Italian MT industry is indeed characterized by the coexistence of a small group of large firms, and a large tier of smaller firms. As emphasized by Rolfo (1993), Italian MT builders are basically single-product firms, and almost all types of products reveal the existence of niches, in which the ability to solve customers' specific problems is essential (Wengel and Shapira 2004). The two largest product specializations are metal-cutting machinery such as machining centers and lathes, and metal-forming machinery such as presses and sheet metal deformation machinery, as confirmed by our dataset (Table 2).

Table 1 indicates that Italian MT producers show high levels of vertical disintegration (0.67) on average. This evidence is in line with general patterns characterizing the broader Italian manufacturing industry, as shown by Arrighetti (1999). The comparison of the standard deviation of the VDIS measure (almost 0.12) with its average value stresses the high heterogeneity of MT producers with respect to their vertical organization choices.

## 5 Econometric results

### 5.1 First step: the SFM

The estimation[17] of the TREMU production model[18] is presented in Table 3.

The $\lambda$ parameter is approximately equal to 1.75, thus revealing that inefficiency actually resides in the

[16] The idea behind the use of this proxy is that the more assets are specific to the set of activities conducted by the firm, the higher are costs are attached in the case of bankruptcy, due to the lower redeployability. In this sense, it would be more costly to finance these kinds of assets (e.g., R&D investments) with debt. Thus, the debt-to-asset ratio should be negatively related to the amount of firm-specific assets.

[17] All estimations and calculations are based on Stata 10.1 and NLOGIT 4.0 environments.

[18] We cross-refer the reader to Sect. 6.1, for a detailed comparison of TREMU with alternative SFM.

**Table 1** Descriptive statistics, 1998–2007

| Variable | Notation | Unit | Mean | SD | p10 | p25 | p50 | p75 | p90 | *N* obs |
|---|---|---|---|---|---|---|---|---|---|---|
| Gross output | $Y$ | Thousands euro | 16,828 | 57,111 | 1,600 | 2,839 | 6,004 | 12,961 | 30,405 | 3,865 |
| Capital stock | $K$ | Thousands euro | 2,453 | 7,812 | 76.5 | 224 | 790 | 2,092 | 4,932 | 3,865 |
| Labor (=size) | $L$ | Number of workers | 98.5 | 323 | 10 | 19 | 41 | 86 | 187 | 3,865 |
| Intermediate inputs and services | $M$ | Thousands euro | 11,383 | 40,438 | 923 | 1,721 | 3,887 | 8,700 | 19,966 | 3,865 |
| Total costs of production | TC | Thousands euro | 17,012 | 59,103 | 1,559 | 2,819 | 6,094 | 13,016 | 30,558 | 3,865 |
| Vertical disintegration | VDIS | Ratio | 0.67 | 0.119 | 0.503 | 0.594 | 0.68 | 0.757 | 0.814 | 3,865 |
| Downward cycle | DCYCLE | Dummy | 0.336 | 0.472 | 0 | 0 | 0 | 1 | 1 | 3,865 |
| Labor cost | $\overline{WAGE}$ | Ratio | 39.4 | 83.5 | 25.4 | 26.9 | 33.1 | 41.7 | 49.9 | 3,865 |
| Debt-to-asset ratio | ASS_UNS | Ratio | 5.74 | 11.3 | 1.19 | 1.83 | 3.12 | 5.71 | 10.7 | 3,363 |
| Volume uncertainty | UNCE | Thousands euro | 1.26 | 2.24 | 0.0318 | 0.151 | 0.532 | 1.53 | 3.03 | 3,393 |

**Table 2** Breakdown of firms by type of production

| Product categories (builders) | *N* firms | *N* obs |
|---|---|---|
| Metal-cutting machines | 175 | 1334 |
| Metal-forming machines | 124 | 925 |
| Unconventional machines | 24 | 180 |
| Welding machines | 2 | 14 |
| Measuring-control machines | 15 | 114 |
| Heat treatment machines | 19 | 143 |
| Mechanical devices | 107 | 844 |
| Electric/electronic equipment | 22 | 179 |
| Tools | 17 | 132 |
| Total | 505 | 3,865 |

data and supporting the adequacy of the frontier model with respect to an average production function which does not take into account the existence of inefficiency, i.e. $u_{i,t} = 0$ for all $i$, $t$. We can conduct some generalized likelihood ratio tests of the form $\mathrm{LR} = -2[\ln L(H_0) - \ln L(H_1)] \sim \chi^2_J$ on the estimated parameters of the TREMU model. First, we can check for the adequacy of the translog specification against the more parsimonious Cobb–Douglas form: the first row of Table 4 supports the choice of the more flexible form. Second, we can conduct a joint test of the significance of the vector of year dummies, $\tau_t$: the second row of Table 4 ensures the significance of the $\tau_t$ vector. Descriptive statistics on the estimated inefficiency scores (obtained via the Jondrow estimator) for the TREMU model are presented in the last row of Table 4. MT builders are 'on average' quite efficient, showing a percentage of inefficiency of almost 7%.

After having recovered the inefficiency scores, $\widehat{u}_{it}^{\mathrm{TREMU}}$, we use them as the measure of performance to investigate the relationship between firm's efficiency and vertical integration in the next section.

### 5.2 Second step: vertical integration and efficiency

In order to investigate the relationship between firms' efficiency and vertical integration, we start from estimating variants of Eq. 11, in which efficiency determines the vertical integration choice by means of OLS.

Bearing in mind that (see Sect. 3.1) the $\widehat{u}_{it}^{\mathrm{TREMU}}$ scores must be interpreted as in deviation from a firm's mean level of output (inefficiency), and in order to control for time-invariant firm characteristics which may be correlated both with the level of inefficiency and the degree of vertical disintegration,[19] we adopt the fixed-effects transformation of Eq. 11 (see Wooldridge 2002, p. 267), by inserting all other variables as deviations from their firm's average: estimates are

[19] Natural candidates may be fixed management quality, type of machine produced, specific differences in upstream/downstream markets.

**Table 3** The TREMU SFM

| Dependent variable: ln$Y$ | | TREMU (MSL) |
|---|---|---|
| Variable | Coefficient | |
| ln $K$ | $\beta_k$ | 0.0086*** |
| | | (0.0028) |
| ln $L$ | $\beta_l$ | 0.1164*** |
| | | (0.0051) |
| ln $M$ | $\beta_m$ | 0.8546*** |
| | | (0.0042) |
| (.5) (ln $K$)$^2$ | $\beta_{kk}$ | 0.0044** |
| | | (0.00173) |
| (.5) (ln $L$)$^2$ | $\beta_{ll}$ | 0.0769*** |
| | | (0.0036) |
| (.5) (ln $M$)$^2$ | $\beta_{mm}$ | 0.1168*** |
| | | (0.0032) |
| (ln $K$) (ln $L$) | $\beta_{kl}$ | −0.00183 |
| | | (0.00185) |
| (ln $K$) (ln $M$) | $\beta_{km}$ | −0.0131*** |
| | | (0.0017) |
| (ln $L$) (ln $M$) | $\beta_{lm}$ | −0.0689*** |
| | | (0.0027) |
| Constant | $\alpha$ | 0.0778*** |
| | | (0.0047) |
| Error parameters | $\sigma^2$ | 0.0110*** |
| | $\lambda$ | 1.7496*** |
| | $\sigma_u$ | 0.0911*** |
| | $\sigma_v$ | 0.0521*** |
| | $\sigma_{\bar{z}}$ | 0.0950*** |
| Year dummies | $\tau_t$ | Yes |
| Firm random terms | $\omega_i$ | Yes |
| Within-group means of $\mathbf{x_{it}}(\bar{\mathbf{x}}_\mathbf{i})$ | $\delta$ | Yes |
| Number of Halton draws | | 1,000 |
| Log-likelihood | | 3,932 |
| Observations | | 3,865 |

Complete table available from authors upon request

$\tau_t$ and $\delta$ estimates omitted to save space

Significance levels: * 10%, ** 5%, *** 1%

listed in Table 5. In specification A1, the degree of vertical disintegration is regressed on the estimated level of inefficiency and the other firms' characteristics. Results reveal a positive relationship between the firm's inefficiency and its degree of vertical disintegration. Higher inefficiency levels lead firms to adopt more disintegrated structures for their production processes; in particular, a 1% increase in the inefficiency level leads to a 0.59% increase in the chosen degree of vertical disintegration.[20]

The value of coefficients referring to other variables is also worthy of comment. The relationship between size and vertical disintegration turns out to be negative, indicating that the larger MT builders are, the more vertically integrated they are. Firms with higher average wages show a lower degree of vertical disintegration, although the relationship is not statistically significant. The degree of asset specificity appears to be positively correlated with vertical integration (we recall that ASS_UNS$_{it}$, the debt-to-assets ratio, is a proxy for the degree of 'un-specificity' of the firm's assets), which matches previous empirical works adopting the transaction costs perspective (see, e.g., Lyons 1995). The estimated coefficient of the UNCE$_{it}$ variable reveals a negative relationship between the level of uncertainty in the final demand and the degree of vertical disintegration. More uncertainty leads MT producers, on average, to control a greater part of their production processes, which is consistent with the prediction of transaction cost economics (see Lafontaine and Slade 2007, p. 657). Lastly, years characterized by a downward trend in aggregate demand are also characterized by a lower degree of vertical disintegration.

Thus, after controlling for a relevant set of firms' characteristics, higher inefficiency levels are systematically related to higher degrees of vertical disintegration. Thus, the coefficient of the $\hat{u}_{it}^{\mathrm{TREMU}}$ scores suggests that more integrated organizations are advantaged.

Although the results capture a systematic pattern of how firms' efficiency levels map into different degrees of vertical integration, this cannot be interpreted as a causal effect: the results may still suffer from problems of endogeneity and reverse causation. We implemented two robustness checks to deal with this problem. First, we estimated the above specification, using the 1-year lagged values of inefficiency instead of contemporaneous values, which should reduce the endogeneity problem. Coefficient $\gamma_{l1}$ in specification

[20] As $\hat{u}_{it}^{\mathrm{TREMU}}$ and UNCE$_{it}$ result from the estimation of econometric models, potential measurement errors stemming from the corresponding regressions may lead to inefficient estimates: for this reason, we re-estimated A1 using the Prais–Winsten method with heteroskedastic panels corrected standard errors (PCSE). The same procedure was applied to the B1 specification. All results are stable and available from authors upon request.

**Table 4** Generalized LR tests on parameters of the TREMU model and inefficiency scores

| Null hypothesis | Restricted vs. unrestricted | Conditions | $\chi^2$ statistics | Critical values (5%) |
|---|---|---|---|---|
| Cobb–Douglas restrictions | (C–D vs. Translog) | $\beta_{np} = 0$ and $\delta_{np} = 0$ for $n, p = K, L, M$ | 724.14 | 21.03 |
| No time dummies | | $\tau_t = 0$ | 146.89 | 18.31 |
| **Inefficiency scores** | **Mean** | **SD** | **Min** | **Max** |
| $\widehat{u}_{it}^{\mathrm{TREMU}}$ | 0.0705 | 0.0413 | 0.0109 | 0.517 |

**Table 5** Efficiency as a determinant of vertical integration

| Dependent variable: $\mathrm{VDIS}_{it}$ | | A1 (OLS-FE) | A2 (OLS-FE) | A3 (OLS-FE) | A4 (IV-GMM) |
|---|---|---|---|---|---|
| Variable | Coefficient | | | | |
| $\widehat{u}_{it}^{\mathrm{TREMU}}$ | $\gamma_1$ | 0.5916*** | | 0.5332*** | 0.1614** |
| | | (0.0367) | | (0.0412) | (0.0659) |
| $\widehat{u}_{i,t-1}^{\mathrm{TREMU}}$ | $\gamma_{l1}$ | | 0.2768*** | 0.0974** | 0.0308 |
| | | | (0.0410) | (0.0421) | (0.0677) |
| $\mathrm{SIZE}_{it}$ | $\lambda_1$ | −0.0155*** | −0.0252*** | −0.0149** | −0.0266*** |
| | | (0.0055) | (0.0063) | (0.0061) | (0.0090) |
| $\overline{\mathrm{WAGE}}_{it}$ | $\lambda_3$ | −0.0032 | −0.0304*** | −0.0043 | −0.0272*** |
| | | (0.0067) | (0.0074) | (0.0075) | (0.0101) |
| $\mathrm{ASS\_UNS}_{it}$ | $\lambda_3$ | 0.0369*** | 0.0404*** | 0.0411*** | 0.0399*** |
| | | (0.0033) | (0.0037) | (0.0036) | (0.0044) |
| $\mathrm{UNCE}_{it}$ | $\lambda_4$ | −0.0100*** | −0.0111*** | −0.0116*** | −0.0107*** |
| | | (0.0018) | (0.0021) | (0.0020) | (0.0028) |
| DCYCLE | $\lambda_5$ | −0.0186*** | −0.0233*** | −0.0178*** | −0.0225*** |
| | | (0.0033) | (0.0036) | (0.0035) | (0.0036) |
| Constant | $\gamma_0$ | −0.0348*** | −0.0110*** | −0.0381*** | −0.0051 |
| | | (0.0032) | (0.0035) | (0.0040) | (0.0078) |
| Fixed-effects transformation | $\eta_i$ | Yes | Yes | Yes | Yes |
| Observations | | 2,973 | 2,664 | 2,664 | 2,664 |
| Log-likelihood | | 3,546 | 3,083 | 3,165 | 3,113 |

| Tests on IV estimates (robust to heteroskedasticity and autocorrelation) | |
|---|---|
| Underidentification; Kleibergen–Paap *rk* LM statistic (*P* value, 1-stage) | 0.0000 |
| Weak identification; Kleibergen–Paap Wald *rk F* statistic (1-stage) | 135.28 |
| Hansen *J* test on overidentifying restrictions (*P* value) | 0.1692 |
| Exogeneity test (OLS vs. IV) (*P* value) | 0.0000 |

SE of coefficients in parentheses

Significance levels: * 10%, ** 5%, *** 1%

A2 is smaller than that of contemporaneous scores, $\gamma_1$ in A1, although the positive and significant relationship is confirmed. Once we introduce both contemporaneous and lagged inefficiency levels, in specification A3, the former ones show a much higher coefficient, which captures almost the entire effect of

**Table 6** Effect of vertical organization on firms' productive efficiency

| Dependent variable: $\widehat{u}_{it}^{\text{TREMU}}$ | | B1 (OLS-FE) | B2 (OLS-FE) | B3 (IV-GMM) |
|---|---|---|---|---|
| Variable | Coefficient | | | |
| $\text{VDIS}_{it}$ | $\theta_1$ | 0.1364*** | | −0.1133 |
| | | (0.0085) | | (0.0799) |
| $\text{VDIS}_{i,t\text{-}1}$ | $\theta_{l1}$ | | 0.0403*** | |
| | | | (0.0092) | |
| SIZE | $\varphi_1$ | −0.0221*** | −0.0254*** | −0.0299*** |
| | | (0.0026) | (0.0030) | (0.0067) |
| $\overline{\text{WAGE}}$ | $\varphi_2$ | −0.0477*** | −0.0544*** | −0.0595*** |
| | | (0.0031) | (0.0036) | (0.0083) |
| ASS_UNS | $\varphi_3$ | −0.0069*** | −0.0020 | 0.0035 |
| | | (0.0016) | (0.0018) | (0.0043) |
| UNCE | $\varphi_4$ | 0.0029*** | 0.0013 | −0.0005 |
| | | (0.0008) | (0.0010) | (0.0016) |
| DCYCLE | $\varphi_5$ | −0.0054*** | −0.0114*** | −0.0131*** |
| | | (0.0016) | (0.0017) | (0.0026) |
| Constant | $\theta_0$ | 0.0714*** | 0.0744*** | 0.0750*** |
| | | (0.0008) | (0.0010) | (0.0013) |
| Fixed-effects transformation | $\eta_i$ | Yes | Yes | Yes |
| Log-likelihood | | 5,728 | 5,025 | 4,642 |
| Observations | | 2,973 | 2,664 | 2,555 |
| Tests on IV estimates (robust to heteroskedasticity and autocorrelation) | | | | |
| Underidentification; Kleibergen–Paap *rk* LM statistic (*P* value, 1-stage) | | | | 0.0000 |
| Weak identification; Kleibergen–Paap Wald *rk* *F* statistic (1-stage) | | | | 22.39 |
| Hansen *J* test on overidentifying restrictions (*P* value) | | | | 0.1515 |
| Exogeneity test (OLS vs. IV) (*P* value) | | | | 0.0010 |

SE of coefficients in parentheses

Significance levels: * 10%, ** 5%, *** 1%

inefficiency on vertical disintegration. Second (specification A4), we instrumented the current and 1-year lagged levels of inefficiency with the inefficiency level at the beginning of the period, $\widehat{u}_{i,1998}^{\text{TREMU}}$, and the current and 1-year lagged inefficiency scores from the pooled SFM in Eq. 3, $\widehat{u}_{it}^{\text{PSF}}$. These variables, which are well correlated with $\widehat{u}_{it}^{\text{TREMU}}$ and $\widehat{u}_{i,t-1}^{\text{TREMU}}$ (see Table 9 in Sect. 6.1), should not in fact be correlated with the $\text{VDIS}_{it}$ variable after demeaning. The generalized method of moments (GMM) estimator is implemented. The *P* value of Kleibergen-Paap *rk* LM test rejects the null hypothesis, thus reassuring us about the identification of the model; the Kleibergen–Paap Wald *rk* weak-identification test confirms that the relationship between the instruments and the potentially endogenous regressors is strong, showing a remarkably high *F* statistic (135.28[21]); and the instruments are valid, as the Hansen *J* statistic, with a *P* value of 0.17, indicates that overidentifying restrictions are not

[21] Critical values tabulated by Stock and Yogo (2005) are well below the reported value.

rejected. However, the exogeneity test rejects the null hypothesis that both $\widehat{u}_{it}^{\mathrm{TREMU}}$ and $\widehat{u}_{i,t-1}^{\mathrm{TREMU}}$ are exogenous ($P$ value $= 0.0000$); thus, the OLS estimates are inconsistent and the IV estimates must be preferred, although they show a smaller but still significant effect from inefficiency to vertical disintegration.

Summing up, these results suggest that, after controlling for the endogeneity of firms' inefficiency, a positive effect from the latter to the degree of vertical disintegration is at work; all else being equal, more inefficient firms select more disintegrated structures. The effect amounts to an elasticity of 0.16%.

Endogeneity may be due either to unobserved time-variant characteristics related to vertical integration and efficiency, or to a true reverse causality from the vertical organization of production to the performance of the firm. In order to assess whether a reverse effect is at work, we estimate the variants of Eq. 12, after the fixed-effects transformation; the results are listed in Table 6. In specification B1, we regress levels of inefficiency on contemporaneous degrees of vertical disintegration, controlling for firms' unobserved heterogeneity and the other characteristics. A 1% change in the degree of vertical disintegration leads to a 0.13% change in the inefficiency level, but given the endogeneity of the VDIS variable in the relationship, this evidence is only suggestive and we need further checks to be able to asses something which is nearer to a causal effect.

Consequently, we first regress the current levels of inefficiency on 1-year lagged degrees of vertical disintegration, $\mathrm{VDIS}_{i,t-1}$, finding that the positive relationship decreases in magnitude (specification B2).[22] Second, we instrument $\mathrm{VDIS}_{it}$ with 1-year lags of the proxy of asset specificity, the measure of uncertainty and firm size. The underidentification ($P$ value) and weak-identification tests show that the equation is identified and that the instruments are well correlated with $\mathrm{VDIS}_{i,t-1}$ ($F$ statistic $= 22.39$). The Hansen $J$ test gives a $P$ value higher than 0.15, indicating that the implemented instruments are valid. Given the low $P$ value of the exogeneity test, the OLS estimates are not consistent and the IV estimates should be preferred to them, indicating an effect which is not significant from $\mathrm{VDIS}_{it}$ to $\widehat{u}_{it}^{\mathrm{TREMU}}$ in the empirical model.[23] Thus, an effect from the organization of production to firms' efficiency is not supported by the data.

Overall, once firms' unobserved heterogeneity, firm size, average wage, degree of asset specificity, proxies for demand uncertainty, economic cycle, and the endogeneity in the relationship have all been controlled for, the evidence provided above clearly indicates the self-selection mechanism of the most efficient firms in vertically integrated structures, while the evidence of an effect from the organization of production to efficiency is not supported by the data.

But why should the most efficient builders of MTs select more integrated structures? One explanation has been provided by the competitive markets' approach with heterogeneous firms, such as the works by Elberfeld (2001) and Antras and Helpman (2004) in which the authors assume higher organizational fixed costs for vertically integrated firms, and higher variable costs for the intermediates faced by disintegrated firms. Holding on to this approach, the most efficient builders of MTs may choose integrated structures, and less efficient ones may choose to outsource part of their production process by buying intermediate inputs from other firms, thus reducing fixed costs but bearing higher marginal costs and staying in the market.[24] Although results may be consistent with this explanation, due to the unavailability of data on input prices for the Italian MT builders, we are not able to perform a direct and rigorous test on the mechanism suggested by Elberfeld (2001) and Antras and Helpman (2004), for example, by estimating a cost function in levels, and we simply look at that theoretical framework as a plausible interpretation for our results.

[22] When both current and lagged degrees of vertical disintegration are included in the equation, only the former have a significant effect on the inefficiency level and the magnitude is in line with that of specification B1. Results are available from the authors upon request.

[23] Note that the result in specification B3 is not due to sample bias, passing from 2,973 to 2,555 observations; in fact, re-running specification B1 on the sample of B3 by means of OLS, the $\mathrm{VDIS}_{it}$ elasticity becomes almost 0.13%. Results are available from the authors upon request.

[24] The assumption of higher fixed organizational costs for integrated firms relates to the additional managerial tasks needed to supervise intermediate stages of the production process; this hypothesis seems reasonable in the MT industry, in which some activities, such as the production of mechanical components or electronic assemblies, require not negligible supervision and coordination efforts.

## 6 Robustness checks

### 6.1 Alternative SFMs

As mentioned in Sect. 3.1, other production models may be adopted to estimate the technical inefficiency of the Italian MT producers. We compared the TREMU model with the average production function, the PSF model in Eq. 3, the TFE and TRE model: estimates are listed in Table 7 and generalized likelihood ratio tests $LR = -2[\ln L(H_0) - \ln L(H_1)] \sim \chi^2_J$ were performed to select the model which minimizes

**Table 7** Alternative SFMs

| Dependent variable: ln $Y$ | | M1 Av PF (OLS) | M2 PSF (ML) | M3 TFE (ML) | M4 TRE (MSL) | M5 TREMU (MSL) |
|---|---|---|---|---|---|---|
| Variable | Coefficient | | | | | |
| ln $K$ | $\beta_k$ | 0.0260*** | 0.0264*** | 0.0097*** | 0.0176*** | 0.0086*** |
| | | (0.0030) | (0.0030) | (0.0037) | (0.0017) | (0.0028) |
| ln $L$ | $\beta_l$ | 0.2249*** | 0.2263*** | 0.1157*** | 0.1510*** | 0.1164*** |
| | | (0.0054) | (0.0055) | (0.0068) | (0.0031) | (0.0051) |
| ln $M$ | $\beta_m$ | 0.7562*** | 0.7544*** | 0.8496*** | 0.8297*** | 0.8546*** |
| | | (0.0047) | (0.0049) | (0.0061) | (0.0026) | (0.0042) |
| (.5) (ln $K$)$^2$ | $\beta_{kk}$ | 0.0057*** | 0.0062*** | 0.0046** | 0.0067*** | 0.0044** |
| | | (0.0021) | (0.0021) | (0.0019) | (0.0012) | (0.00173) |
| (.5) (ln $L$)$^2$ | $\beta_{ll}$ | 0.1306*** | 0.1320*** | 0.0779*** | 0.1000*** | 0.0769*** |
| | | (0.0054) | (0.0055) | (0.0051) | (0.003) | (0.0036) |
| (.5) (ln $M$)$^2$ | $\beta_{mm}$ | 0.1229*** | 0.1234*** | 0.1176*** | 0.1190*** | 0.1168*** |
| | | (0.0057) | (0.0057) | (0.0053) | (0.0025) | (0.0032) |
| (ln $K$) (ln $L$) | $\beta_{kl}$ | −0.0028 | −0.0031 | −0.0018 | −0.0052*** | −0.00183 |
| | | (0.0026) | (0.0026) | (0.0024) | (0.0012) | (0.00185) |
| (ln $K$) (ln $M$) | $\beta_{km}$ | −0.0030 | −0.0031 | −0.0133*** | −0.0094*** | −0.0131*** |
| | | (0.0023) | (0.0023) | (0.0024) | (0.0011) | (0.0017) |
| (ln $L$) (ln $M$) | $\beta_{lm}$ | −0.1204*** | −0.1210*** | −0.0689*** | −0.0863*** | −0.0689*** |
| | | (0.0048) | (0.0049) | (0.0043) | (0.0022) | (0.0027) |
| Constant | $\alpha$ | 0.0273*** | 0.0742*** | −0.2081*** | 0.0793*** | 0.0778*** |
| | | (0.0067) | (0.0127) | (0.0651) | (0.0046) | (0.0047) |
| Error parameters | $\sigma^2$ | 0.0144[a] | 0.0165*** | 0.0110*** | 0.0109*** | 0.0110*** |
| | $\lambda$ | n/a | 0.5237*** | 2.3561*** | 1.6576*** | 1.7496*** |
| | $\sigma_u$ | n/a | 0.0597*** | 0.0966*** | 0.0895*** | 0.0911*** |
| | $\sigma_v$ | n/a | 0.1140*** | 0.0410*** | 0.0540*** | 0.0521*** |
| | $\sigma_{\bar{z}}$ | n/a | n/a | n/a | 0.1193*** | 0.0950*** |
| Year dummies | $\tau_t$ | Yes | Yes | Yes | Yes | Yes |
| Firm dummies | $\alpha_i$ | No | No | Yes | No | No |
| Firm random terms | $\omega_i$ | No | No | No | Yes | Yes |
| Within-group means of $X_{it}$ ($\bar{\mathbf{x}}_{\mathbf{it}}$) | $\delta$ | No | No | No | No | Yes |
| Number of Halton draws | | n/a | n/a | n/a | 1,000 | 1,000 |
| Log-likelihood | | 2,726 | 2,727 | 4,843 | 3,807 | 3,932 |
| Observations | | 3,865 | 3,865 | 3,865 | 3,865 | 3,865 |

SE of coefficients in parentheses

$\tau_t$ and $\delta$ estimates omitted to save space. Complete table available from authors upon request

Significance levels: * 10%, ** 5%, *** 1%

[a] SE not computed

**Table 8** Generalized LR tests on parameters of SFM

| Null hypothesis | Restricted vs. unrestricted | Conditions | $\chi^2$ statistics | Critical values (5%) |
|---|---|---|---|---|
| No inefficiency | (M1 vs. M2) | $\sigma_u = 0$ | 1.65 | 2.71 (1.63 at the 10%)[a] |
| No firm dummies | (M2 vs. M3) | $\alpha_i = 0$ | 4,232.96 | 557.3 |
| No inefficiency | (LSDV vs. M3) | $\sigma_u = 0$ | 171.14 | 2.71[a] |
| No Mundlak term effects | (M4 vs. M5) | $\delta = 0$ | 249.95 | 16.92 |

[a] This test is at the boundary of parameter space ($\sigma_u$); the critical value comes from Kodde and Palm (1986)

misspecification biases (Table 8). Specification M1 reports the technology parameters of an 'average production function' estimated via OLS ($u_{i,t} = 0$ for all $i$, $t$). This model can be tested against a PSF model, which explicitly takes technical inefficiency into account. The LR test of $\sigma_u = 0$ generates a $\chi^2 = 1.65$ which supports $\sigma_u$ being different from 0 at the 10% level; the introduction of firms' effects in the frontier model changes the results. The TFE model, which may be specified as

$$y_{it} = \alpha_i + \boldsymbol{\beta}'\mathbf{x_{it}} + v_{it} - u_{it}, \tag{16}$$

where

$$v_{it} \sim \text{i.i.d.}\, N(0, \sigma_v^2),\; u_{it} \sim \text{i.i.d.}\, N^+(0, \sigma_u^2), \tag{17}$$

and $\alpha_i$ is a vector of firm dummies, is estimated via ML and reported in the third column of Table 7. This model allows time-invariant heterogeneity (firms' effects) to be correlated with inputs, but the vector of firm dummies creates an incidental parameter problem (Lancaster 2000): with small $T$, estimates of $\alpha_i$ are inconsistent and subject to small sample bias, and given that $\widehat{\epsilon}_{it} = y_{it} - \widehat{\alpha}_i - \widehat{\boldsymbol{\beta}}'\mathbf{x_{it}}$, this bias may directly affect the estimated inefficiency scores.

The LR test in the second row of Table 8 strongly rejects the possibility that firms' effects are jointly not significant in the model. In addition, a test of significance of the $\sigma_u$ parameter in the M3 model reveals that inefficiency actually resides in the data (third row of Table 8).

An alternative way of including firms' effects in the frontier is by implementing the TRE model (specification M4); however, as stated in Sect. 3.1, TRE assumes that firm-specific heterogeneity is uncorrelated with inputs. Both TFE and TRE models may be chosen to estimate the technical inefficiency of the Italian MT builders, and we need a test in order to select the model which fits the data best. However, to our knowledge, there are no direct ways of testing between the TFE and TRE models in the context of stochastic frontiers, and we rest on an 'indirect' test. We estimated the TREMU in specification M5, and a strong rejection of the null hypothesis that the Mundlak terms are jointly equal to zero should be viewed as favoring TFE over TRE. Actually, this result is borne out by the test reported in the fourth row of Table 8.

Overall, the TREMU model is our favorite specification for several reasons: it allows us to control for the heterogeneity of firms, separating it from time-variant technical inefficiency, thus lessening the heterogeneity bias which affects the PSF model; like the TFE model, TREMU allows for part of the individual effect to be correlated with inputs, thus overcoming a major problem in the TRE model; this is also confirmed by the fact that technology parameters of the TREMU model result to be much closer to the ones of the TFE model than to those of the TRE model; finally, unlike TFE, which produces biased estimates of inefficiency scores, TREMU does not suffer from the incidental parameter problem.

Table 9 lists Pearson's and Spearman's rank correlation coefficients among estimates of the inefficiency scores. Interestingly enough, when we compute within-group deviations from the firms' average inefficiency obtained via the PSF model, $\widetilde{\widehat{u}_{it}^{\text{PSF}}}$, and calculate correlation coefficients with the other sets of scores, the $\widetilde{\widehat{u}_{it}^{\text{PSF}}}$ are much more in line with the inefficiency scores from the TFE, TRE and TREMU models than with those from the PSF. This evidence supports the idea (Sect. 3.1) that the inefficiency scores from TFE, TRE and TREMU should be interpreted, as being in deviation from the firm's average inefficiency level.

## 6.2 The one-step approach

The one-step estimation is frequently adopted in empirical works which analyze the determinants of inefficiency, by modeling the parameters of the

**Table 9** Correlation coefficients among sets of scores

| | $\widehat{u}_{it}^{\text{PSF}}$ | $\widehat{u}_{it}^{\text{TFE}}$ | $\widehat{u}_{it}^{\text{TRE}}$ | $\widehat{u}_{it}^{\text{TREMU}}$ | $\widetilde{\widehat{u}}_{it}^{\text{PSF}}$ |
|---|---|---|---|---|---|
| Pearson's correlation coefficients | | | | | |
| $\widehat{u}_{it}^{\text{PSF}}$ | 1 | | | | |
| $\widehat{u}_{it}^{\text{TFE}}$ | 0.7116 | 1 | | | |
| $\widehat{u}_{it}^{\text{TRE}}$ | 0.7126 | 0.9274 | 1 | | |
| $\widehat{u}_{it}^{\text{TREMU}}$ | 0.7022 | 0.8800 | 0.9854 | 1 | |
| $\widetilde{\widehat{u}}_{it}^{\text{PSF}}$ | 0.7127 | 0.9692 | 0.8927 | 0.8481 | 1 |
| Spearman's rank correlation coefficients | | | | | |
| $\widehat{u}_{it}^{\text{PSF}}$ | 1 | | | | |
| $\widehat{u}_{it}^{\text{TFE}}$ | 0.5820 | 1 | | | |
| $\widehat{u}_{it}^{\text{TRE}}$ | 0.6104 | 0.9328 | 1 | | |
| $\widehat{u}_{it}^{\text{TREMU}}$ | 0.6007 | 0.8803 | 0.9818 | 1 | |
| $\widetilde{\widehat{u}}_{it}^{\text{PSF}}$ | 0.5720 | 0.9875 | 0.9146 | 0.8624 | 1 |

inefficiency distribution with third variables. Given that the estimation of Eq. 12 in a separate second step may have limitations, we also estimated the TFE model parameterizing the variance of the inefficiency distribution (half-normal) with the measure of vertical disintegration and the controls, jointly estimating the frontier parameters and the effects of third variables on inefficiency via ML estimation[25]; results are shown in Table 10. The magnitudes of coefficients are not directly comparable with those of specifications B1–B3, and they should be interpreted as correlations with the variance of the inefficiency distributions; the signs are consistent with those obtained from two-step estimations. The main result is that once the (1-year) lagged measure of VDIS is included in the regression, the effect on the variance of the inefficiency distribution disappears (specification C2), which is consistent with the other-way-round effect, stemming from a self-selection mechanism. This fact reassures us about the results obtained via the IV-GMM approach.

Moreover, the two-step estimation procedure allows us to control for the endogeneity in the relationship between vertical integration and efficiency and to compute conditional marginal effects in the second step of the analysis, which are both central issues in the paper.

## 7 Concluding remarks

In this paper, we study the relationship between vertical integration and firm efficiency in the Italian MT industry. The link may definitely be the result of a two-way causality, which has been neither comprehensively included in a single theoretical framework nor systematically assessed in empirical works. We empirically ground our analysis on a sample of about 500 Italian MT producers and, in order to disentangle the direction of causation, we develop the analysis in a two-step econometric framework. In the first step, we estimate technical inefficiency via a SFM, taking the unobserved heterogeneity among firms into account, in light of the latest frontier models for panel data suggested by Greene (2005). In the second step, we investigate the relationship between the degree of vertical integration and technical efficiency, by means of two equations using instrumental variables to control for endogeneity. Once firms' unobserved heterogeneity, firm size, average wage, degree of asset specificity, a proxy for demand uncertainty and the economic cycle are controlled for, the evidence indicates a self-selection mechanism of the most efficient firms in vertically integrated structures; conversely, the evidence of an effect from the organizational mode to efficiency is not supported by

[25] Both the TFE and TREMU models are difficult to be estimated with the parameterized variance of the inefficiency distribution and may result in unreliable estimates of the coefficients. Following Greene (2008), we performed the one-step estimation with the TFE model: to our knowledge, there are no applications of TREMU with third variables affecting the parameters of the inefficiency distribution. We do not report the frontier parameters in specifications C1 and C2 for reasons of space. Complete results are available from authors upon request.

**Table 10** Effect of vertical organization on firms' productive efficiency: TFE, one-step estimation

| Dependent variable: $\sigma_{u_{it}}$ | | C1 (TFE, one-step ML) | C2 (TFE, one-step ML) |
|---|---|---|---|
| Variable | Coefficient | | |
| $VDIS_{it}$ | $\theta_1$ | 12.9162*** | |
| | | (1.1053) | |
| $VDIS_{i,t\text{-}1}$ | $\theta_{l1}$ | | 0.2507 |
| | | | (0.3975) |
| SIZE | $\varphi_1$ | −3.2335*** | −3.4736*** |
| | | (0.3197) | (0.2710) |
| $\overline{\text{WAGE}}$ | $\varphi_2$ | −3.4139*** | −4.2581*** |
| | | (0.3003) | (0.2969) |
| ASS_UNS | $\varphi_3$ | −0.2694* | 0.1555 |
| | | (0.1420) | (0.1068) |
| UNCE | $\varphi_4$ | 0.2223*** | 0.0847* |
| | | (0.0651) | (0.0507) |
| DCYCLE | $\varphi_5$ | 0.1986 | −0.3382** |
| | | (0.2056) | (0.1385) |
| Constant | $\theta_0$ | 0.1958*** | 0.0785 |
| | | (0.0443) | (0.0511) |
| Fixed-effects in the frontier | $\alpha_i$ | Yes | Yes |
| Log-likelihood | | 4,211 | 3,773 |
| Observations | | 2,973 | 2,664 |

SE of coefficients in parentheses

Significance levels: * 10%, ** 5%, *** 1%

the data. The result of the self-selection mechanism is robust to the use of instrumental variables in a GMM approach, which takes the endogeneity of inefficiency into account, showing an effect which amounts to an elasticity of 0.16%.

The results are relevant and may be interpreted in the light of models proposed in the literature on industrial organization and international trade (Elberfeld 2001; Antras and Helpman 2004): the most efficient builders of MTs choose integrated structures, while less efficient firms choose to outsource part of their production process by buying intermediate inputs from other firms. The most efficient firms may exploit their advantage in order to control a greater part of the production chain, maybe resting on a greater coordination among different phases (Kogut and Zander 1996), a deeper control over the innovation process and tailored intermediate inputs (Grossman and Hart 1986). This organizational form may be mostly advantaged in uncertain environments (Lafontaine and Slade 2007) characterized by fluctuations in the aggregate demand, like the Italian MT industry. Leaving some phases of the production process to 'outside'—which has been documented as one of the most frequent business practices in the last few decades—may seem to be a rational choice for less efficient firms in order to deal with some segments of demand.

Overall, this paper contributes to better understanding the link between the vertical organization of production and firms' efficiency, exploring—to our knowledge for the first time—both directions of causality. It also contributes to a better understanding of the functioning of the Italian MT industry, in which heterogeneous firms characterized by different levels of efficiency and organizational forms coexist.

**Acknowledgements** We benefited from the comments of three anonymous referees. We also thank Davide Castellani, Christopher L. Gilbert, Antonio Alvarez, Paolo Polinori, Marco Grazzi, Giovanni Dosi, Francesca Galli, the R.O.C.K. group at the University of Trento and participants at seminars at the University Trento (2010), Pisa (Sant'Anna School of Advanced Studies, 2011) and conferences in Pisa (EWEPA, 2009), Lecce (Industrial Organization Workshop, 2009) and Perugia (AISSEC, 2009) for useful comments and suggestions. The usual disclaimer applies. Fabio Pieri gratefully acknowledges financial support by the Universities of Perugia and Trento in the academic years 2008–2009 and 2009–2010.

## A Data Appendix

We exploit an original dataset, compiled by recovering data from several sources. The list of MT producers is from UCIMU, the Italian Machine Tools, Robots and Automation Manufacturers Association, and includes information on firms' type of production. Information on output, inputs and other firm-level characteristics are from Bureau Van Dijk's AIDA dataset, which contains balance sheet information for firms with turnovers of over 500,000 euro. Deflators for output, intermediate inputs and capital stock, respectively, were computed from the value of production and investments series published by ISTAT[26] at sectoral level.

Based on the reference list provided by UCIMU, we collected balance sheet data for 524 firms and 5,240 observations from Bureau Van Dijk's AIDA dataset. The number of observations with non-missing values for output and inputs amounted to 3,767 observations. We detected 10 outliers by estimating a translog production function via OLS and analyzing the resulting residuals (observations with very strange values in output or inputs in an year, or with standardized residuals which were lower or greater than |5|); they were excluded from the analysis. Conversely, we were able to recover 108 more observations by using linear interpolation to fill the gaps in the series of output and inputs for all the observations which were missing in a given year, but which had non-missing observations for the year before and the year after the missing one. These preliminaries left us with a sample amounting to 505 firms and 3,865 observations (unbalanced panel) with information on output and inputs, for the period 1998–2007. Unfortunately, a higher number of missing observations affects the proxies for asset specificity $ASS\_UNS_{it}$, and demand uncertainty $UNCE_{it}$, which further reduce the dataset to 401 firms and 2,973 observations with full information on all relevant variables. Nonetheless, in order to exploit all available information, we used the 3,865 observations with data for output and inputs to estimate the parameters of the frontier model and recover the inefficiency scores.

Comparing the size distribution (in terms of employees) of firms surveyed by UCIMU in the industry report of 2006 with that shown by our data (Table 11), the analyzed sample weakly over-represents medium-sized firms and slightly under-represents small ones. The geographical distribution of the firms clearly depicts a situation in which the largest percentage of MT facilities is in Northern Italy: according to UCIMU, in 2006, Lombardia (the region of Milano) accounts for almost half the production units; this evidence is supported in our dataset, where almost 53% of observations are located in Lombardia. Overall, the descriptive evidence on size and location in few geographical regions is in line with previous studies by Rolfo (1993) and Wieandt (1994).

In view of this evidence, we are confident that our sample describes the industry in question fairly, capturing its most important characteristics.

**Table 11** Sample versus UCIMU industry report, 2006

| | UCIMU—industry report (%) | Sample (%) |
|---|---|---|
| Size classes (employees) | | |
| ≤50 | 63.10 | 57.29 |
| 50:100 | 14.80 | 21.23 |
| >100 | 22.10 | 21.48 |
| Regions | | |
| Lombardia | 46.30 | 53.20 |
| Triveneto[a] | 17.40 | 13.94 |
| Emilia-Romagna | 16.10 | 10.86 |
| Piemonte | 12.80 | 14.21 |
| Other regions | 7.40 | 7.79 |

[a] Triveneto = Veneto + Friuli + Trentino Alto − Adige

[26] See the ISTAT web page, http://www.istat.it/conti/nazionali.

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