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How Heterogeneous Are the Determinants of Total Factor Productivity in Manufacturing Sectors? Panel-Data Evidence from Vietnam

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Abstract: One of the remaining challenges in explaining differences in total factor productivity is heterogeneity between sectors and within a specific sector in terms of labor and capital. This paper employs the generalized method of moments (GMM) to identify factors that affect total factor productivity across 21 manufacturing sectors and to clarify the heterogeneous determinants of total factor productivity within manufacturing sectors for the period 2010–2015. Our estimations show that large firms have significantly greater total factor productivity levels than small firms in some fragmentations of firms in terms of both labor and total capital and in some manufacturing sectors. It is suggested that firm characteristics should be considered by the government in establishing relevant policies for enhancing firm productivity.

Keywords: total factor productivity; panel causality; heterogeneity; manufacturing sector; Vietnam

JEL Classification: L25; O33; L60; C33

1. Introduction

Given the crucial role of total factor productivity (TFP) in economic growth and development, its determinants have been examined intensively in the relevant literature using a vast number of approaches. These include, for example, the "vintage effect" (Kendrick 1961; Hulten 1992; Hulten and Wykoff 1980; Harper 2007), the learning-by-doing effect (Jovanovic 1982; Pakes and Ericson 1998), resource-based theories (Penrose 1959; Wernerfelt 1984; Barney 2000, 2001), and a "neo-Schumpeterian" growth approach (Aghion and Howitt 2006). As a consequence, the literature on TFP determinants faces the problems of the "open-endedness" of alternative theories that can be applied and provides controversial results in empirical research (Brock and Durlauf 2001). This is because firms within and among sectors are not homogenous in terms of their size. Different levels of labor and capital use lead to different TFP levels. Therefore, taking into account the "within" and "between" heterogeneities in examining TFP is needed. In addition, many of these previous studies focused on the determinants of TFP in developed countries, as detailed panel data at the firm and sector levels are not available in many developing or emerging economies.

This article is aimed at filling in this gap in the literature. Our analysis is based on panel data from the Vietnam Annual Enterprise Survey in 2010–2015. The data have been collected for years using the same sampling method and questionnaire. We focus on the manufacturing sectors, as they have been the main engine for economic growth in Vietnam during the last several years. We construct a production dataset that allows us to estimate TFP levels. Then, key internal TFP determinants are examined. Our estimations, in general, show that large firms have significantly greater TFP levels than small firms in some fragmentations of firms in terms of both labor and total capital and in some manufacturing sectors.

The paper contributes to the literature in several ways. First, our work extends the current literature (Castellani and Giovannetti 2010; Kreuser and Newman 2018; Kim 2018; Ngo and Tran 2020; Ngo and Nguyen 2019; Giang et al. 2019) by accounting for heterogeneity in examining the determinants of TFP at the firm level in a dynamically emerging economy. Second, we examine the TFP determinants in detail by exploring the issues at the levels of 21 manufacturing sectors, and not at level of the aggregated industry. Third, our estimation model is explored using a generalized method of moments (GMM) system estimator, which takes into account the possible endogeneity of some regressors. Fourth, our paper contributes to the empirical results relating to the endogenous growth theory as proposed by Evans (1998), especially in terms of manufacturing sectors within a specific country.

The remaining part of the article is structured as follows. Section 2 reviews the theoretical considerations and empirical evidence. Section 3 describes the data and methods employed in our study. Section 4 discusses the findings. Section 5 concludes the study.

2. Literature Review

A review of the literature on the determinants of enterprise productivity has been provided by Syverson (2011). In his paper, Syverson (2011) pointed out several factors relating to managerial practice/talent (Bloom and Reenen 2007, 2010), higher qualified labor and capital inputs (Ilmakunnas et al. 2004; Sakellaris and Wilson 2004; Van Biesebroeck 2003), information technology and R&D (see for example Jorgenson et al. 2005, 2008; Oliner et al. 2007; Aw et al. 2008), learning-by-doing (Thornton and Thompson 2001), product innovation (Bartel et al. 2007; Bernard et al. 2010), and firm structure decisions (Bloom and Reenen 2010; Forbes and Lederman 2010). External drivers of productivity differences are also listed such as productivity spillovers (Martin et al. 2011), horizontal linkages (Nichter and Goldmark 2009), competition (Foster et al. 2008; Ali and Peerlings 2011), deregulation or proper regulation (Bridgman et al. 2009; Fabrizio et al. 2007; Brown et al. 2006), flexible input markets (Maksimovic and Phillips 2001; Hsieh and Klenow 2009; Bartelsman et al. 2009).

Since the work of Syverson (2011), several empirical studies have explored further potential determinants and in many directions (see, for example, Kreuser and Newman 2018; Kim 2018; Botrić et al. 2017; Satpathy et al. 2017; Venturini 2015; İmrohoroğlu and Tüzel 2014; Mohnen and Hall 2013). Kreuser and Newman (2018), using a firm-level sample of the South African manufacturing sector, found that there is heterogeneity of growth across subsectors. The authors also found a positive relationship between firm size and productivity level. Kim (2018) investigated firm heterogeneity in productivity sources across technology sectors for Japanese manufacturers. In this regard, large firms were found to be more productive. Besides, firm heterogeneity in productivity varied considerably across the technology sectors. Satpathy et al. (2017), using a sample of 616 Indian manufacturing companies from 1998–1999 to 2012–2013, found that the size of firms is important for productivity across the sub-industries. Venturini (2015) studied the role of technology spillovers in the productivity growth of OECD countries and found that both forms of technologically advanced capital (Information and communications technology (ICT) and R&D) influence total factor productivity (TFP) over the long run. İmrohoroğlu and Tüzel (2014), exploring publicly traded firms in the United States between 1963 and 2009, showed that productivity is strongly related to several firm characteristics, such as size, the book-to-market ratio, investment, and hiring rate. Mohnen and Hall (2013) considered four types of innovations, namely: product, process, organizational, and marketing innovations in explaining productivity. The authors concluded that, given the imperfect measurement of innovation and the simultaneity of different types of innovation, it is difficult to isolate the individual effect of each. However, the authors found that some complementary seems to exist between them.

While we expect these determinants to be potentially relevant in the case of enterprises in developing countries, an emerging trend to consider is the heterogeneity of firms as indicated in Dhawan (2001), Castellani and Giovannetti (2010), Cao et al. (2017), Kreuser and Newman (2018), Kim (2018), and Ngo and Tran (2020). The heterogeneity of firms is said to be important in the sense that it composes the firms' characteristics (Kim 2018; Lu et al. 2017), and this affects the firm's productivity. Heterogeneity can be observed in terms of labor, capital between the large firms and the small ones, and in terms of efficiency between efficient firms and inefficient ones (Jovanovic 1982), and terms of investment decision (Head and Ries 2003). Firms are also heterogeneous in terms of the quality of managers and workers (Bloom and Reenen 2010), in terms of the level of international integration (Melitz 2003) and diversification of trading activities as well (Castellani and Giovannetti 2010). Last but not least, by investing in innovation activities, firms are differentiated in terms of technological level and learning (Castellani et al. 2010; Constantini and Melitz 2008; Goedhuys 2007). In this context, the implications from the heterogeneity of firms are taken into account when examining the determinants of productivity. In other words, determinants of productivity now need to be screened through the lens of firm heterogeneity in terms of labor and capital levels. From the above theoretical considerations, we examine the determinants of productivity of Vietnamese enterprises related to traditional factors, such as firm size, firms' ages, labor quality, and capital stock, which are examined in the context of firm heterogeneity.

3. Data and Methods

3.1. Data

We used panel data from the Vietnam Annual Enterprise Survey (VAES) in 2010–2015. This annual survey is managed by the Vietnamese General Statistical Office (GSO) and collects firms' information, such as labor and wages, assets and liabilities, and business performances.

All business entities (enterprises having a business account, and established under the regulations of the State Enterprise Law, Cooperative Law, Enterprise Law, and Foreign Investment Law) in the manufacturing sectors are surveyed. As each firm was assigned a tax code, we used this information to merge annual data to establish a panel dataset. We followed the sector and subsector classification as in Ngo and Tran (2020), Ngo and Nguyen (2019), and United Nations Statistical Division (2008). We kept only firms that have not changed their manufacturing sectors during the period 2010–2015, and firms with positive values of (1) value-added (VA), (2) intermediate materials, and (3) equity. We then eliminated outliers and anomalies by controlling for outliers on value-added, costs of materials, and total assets. Finally, we eliminated related sectors with a number of observations of less than 200 in total. Finally, we obtained the final dataset by dropping missing years. Several studies that used this dataset can be listed, such as Newman et al. (2015), Ngo and Nguyen (2019), Ngo and Tran (2020), and Tran et al. (2019).

3.2. TFP Estimation

We prefer the methodology developed by Ackerberg et al. (2006) (Ackerberg, Ackerberg, Dan, Kevin Caves, and Garth Frazer (AFC)), which is an extension of the technique by Levinsohn and Petrin (2003) for estimating TFP. The AFC procedure solves the problem of endogeneity, which may come from a part of the TFP affected by changes in the factor input decisions, and possible collinearity that exists between labor and proxy variables for the instruments. In addition, the paper employs the AFC procedure with the value-added method. Further, we use intermediate raw material as a proxy variable to ward off the bias problem as mentioned by Ackerberg et al. (2006).

3.3. Model Specification

In the current study, our empirical model of the key determinants of TFP follows the framework by Evans (1998), Bernard and Jensen (1999), Clerides et al. (1998), Kreuser and Newman (2018), Kim (2018), and Giang et al. (2019).

Size: Several studies have found that firm size has a positive relationship with TFP thanks to the accumulation of knowledge of larger companies (the learning-by-doing effects; see: Van Biesebroeck (2005), İmrohoroğlu and Tüzel (2014), Malerba (1992), Lee and Tang (2001), and Jovanovic and Nyarko (1996)). On the other hand, studies by Williamson (1967), Tornatzky and Fleischer (1990), and Kim (2018) have concluded that small firms have higher productivity or efficiency due to their lean organizational structure. The size of a firm is usually calculated as the logarithm of total workers of the firm (Giang et al. 2019; Giang et al. 2018; Kreuser and Newman 2018).

An "age" variable is usually included to measure whether younger plants produce with greater efficiency and better technology than older plants (a vintage capital effect); or if through learning-by-doing productivity increases as the plant ages (Jovanovic and Nyarko 1996).

Furthermore, the measure of the capital stock used (Harris and Drinkwater 2000; Söderbom and Teal 2004) should, in theory, be adjusted to take account of vintage effects, which means the deterioration of used capital, and because new capital embodies the latest technology (leading to obsolescence in older vintages).

Isaksson (2007), in his extensive review on TFP determinants, argued that an increase in the quality of labor enhances absorptive capacity and thus technology transfer. The average wage level is used to capture the effect of labor quality (Castellacci 2007; Jung and Lee 2010; Kim 2018).

Kreuser and Newman (2018) also included value-added as an explanatory variable in the model of TFP determinants. We adjust value-added by the number of workers to minimize the problem of firms' heterogeneity in terms of labor size.

The empirical model of the determinants of TFP has the following form:

$$TFP_{it} = \alpha + \delta X_{it-1} + \phi TFP_{it-1} + \sum\nolimits_j \delta\phi_j Time_j + \varepsilon_{it} \tag{1}$$

where X is a vector of firm characteristics and TFP is the total factor productivity. t and i denote year and firm, respectively, in the model. The firm-level characteristics include capital stock (fixed capital), labor (size of employment), human capital (wage level), and firm age (years of operation). Besides, we include the total factor productivity of the previous year, mainly to deal with the possible endogeneity problem (Kim et al. 2009; Giang et al. 2018). We estimated Equation (1) for 21 manufacturing sectors separately.

The endogeneity problem may exist in estimating determinants of TFP. Value-added per worker can be endogenous, in addition to the total factor productivity of the previous year. To obtain consistent and unbiased estimates of regression coefficients, we adopted the dynamic panel generalized method of moments (GMM) estimation approach (Blundell and Bond 1998; Arellano and Bond 1991). This estimator transforms the regression variables by first differencing and removes the time-invariant characteristics (firm-level fixed effects). In practice, we allow control variables including the variables of capital–labor ratio and the number of workers to be predetermined, and use their lagged values as exogenous instruments in the GMM estimation. Other control variables, such as a firm's age and dummies for years, are treated as strict exogenous variables. The correct application strictly relies on the assumption of autocorrelation (Roodman 2009), which is largely taken care of with the lagged dependent variables as predictors. We also care about the assumptions on the over-identification and erogeneity of instruments to produce valid estimates.

4. Empirical Results

4.1. TFP Estimation Results

Table 1 presents sample means and standard deviations of variables in the Cobb–Douglas production function model.

Table 1. Summary statistics for variables in Cobb–Douglas production function estimation.

Sector	Number of Observations	Value-Added (ln)		Fixed Capital (ln)		Labor (ln)		Raw Material Expenses (ln)	
		Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
10: Food products	5556	14.123	1.923	10.970	1.829	4.845	1.335	16.120	2.076
11: Beverages	558	14.857	2.260	11.291	1.949	4.775	1.070	15.551	2.169
13: Textiles	2322	13.880	1.763	10.512	1.768	4.726	1.188	15.357	1.829
14: Wearing apparel	5208	14.755	1.622	10.261	1.481	5.896	1.327	15.341	1.622
15: Leather and related products	1746	15.359	1.770	10.910	1.808	6.427	1.616	16.069	1.790
16: Wood and products of wood/cork	2034	13.169	1.471	9.910	1.453	4.287	1.033	14.811	1.650
17: Paper and paper products	2016	13.704	1.523	10.612	1.437	4.403	1.041	15.486	1.437
18: Printing and reproduction of recorded media	1122	13.368	1.426	9.730	1.466	4.094	0.976	14.561	1.429
20: Chemicals and chemical products	2136	14.234	1.710	11.134	1.575	4.268	1.118	15.884	1.826
21: Pharmaceuticals, medicinal chemicals	618	15.017	1.561	11.707	1.351	5.140	1.051	16.046	1.533
22: Rubber and plastics products	3258	14.213	1.575	10.999	1.392	4.728	1.149	15.784	1.542
23: Other non-metallic mineral products	4332	13.799	1.684	10.583	1.664	4.710	1.116	14.887	1.829
24: Basic metals	714	14.008	1.865	11.386	1.778	4.456	1.215	16.377	1.970
25: Fabricated metal products	3828	13.577	1.654	10.512	1.510	4.251	1.142	15.151	1.601
26: Computer, electronic and optical products	852	15.312	1.800	11.969	1.745	5.885	1.497	16.541	2.046
27: Electrical equipment	1224	14.473	1.728	11.464	1.544	4.907	1.331	16.158	1.847
28: Not-yet-classified machinery and equipment	942	13.478	1.697	10.557	1.558	4.241	1.187	14.907	1.566
29: Motor vehicles, trailers and semi-trailers	522	15.176	1.757	11.946	1.512	5.393	1.244	16.575	1.802
30: Other transport equipment	654	14.759	2.071	11.645	1.803	5.219	1.390	16.165	2.025
31: Furniture	2856	14.213	1.539	10.660	1.427	5.214	1.253	15.566	1.557
34: Other manufacturing	1080	14.209	1.688	10.550	1.564	5.133	1.323	15.203	1.704

Source: authors' calculation from the Vietnam Annual Enterprise Survey (VAES) 2010–2015.

We estimated the Cobb–Douglas model in Section 3.2 for the 21 sectors. The results in Table 2 indicate that employees (in the natural logarithm) and capital (in the natural logarithm) are significant at the 1 percent level in most sectors.

Table 2. Estimation results of Cobb–Douglas production function using Ackerberg–Caves–Frazer estimator, 2010–2015.

VARIABLES	Sector 10	Sector 11	Sector 13	Sector 14	Sector 15	Sector 16	Sector 17
Dependent variable: value-added (logarithm)							
Capital (ln)	0.517 ***	0.800 ***	0.473 ***	0.0341	0.139 ***	0.389 ***	0.326 ***
	(0.0513)	(0.145)	(0.0192)	(0.0227)	(0.0362)	(0.0349)	(0.0493)
Labor (ln)	0.712 ***	0.605 *	0.755 ***	1.105 ***	0.931 ***	0.901 ***	1.041 ***
	(0.0724)	(0.314)	(0.0332)	(0.0378)	(0.0385)	(0.0862)	(0.109)
Observations	4865	485	2010	4445	1525	1820	1770
Wald test statistic of constant returns to scale	85.48	5.162	152.7	50.19	24.73	23.71	30.35
Sargan–Hansen test statistic	4.19×10^{-9}	3.87×10^{-8}	6.84×10^{-9}	3.03×10^{-8}	2.89×10^{-8}	1.45×10^{-9}	1.78×10^{-7}
VARIABLES	**Sector 18**	**Sector 20**	**Sector 21**	**Sector 22**	**Sector 23**	**Sector 24**	**Sector 25**
Capital (ln)	0.260 ***	0.621 ***	0.162	0.426 ***	0.363 ***	0.476 ***	0.482 ***
	(0.0596)	(0.0328)	(0.209)	(0.0448)	(0.0659)	(0.0138)	(0.0429)
Labor (ln)	1.117 ***	0.597 ***	1.372 ***	0.789 ***	0.986 ***	0.792 ***	0.490 ***
	(0.179)	(0.0577)	(0.368)	(0.0562)	(0.111)	(0.0215)	(0.108)
Observations	970	1825	525	2765	3770	620	3360
Wald test statistic of constant returns to scale	8.442	51.99	7.319	107.8	52.50	219.6	0.0583
Sargan–Hansen test statistic	4.93×10^{-8}	9.18×10^{-9}		6.12×10^{-9}	1.82×10^{-8}		6.456

Table 2. *Cont.*

VARIABLES	Sector 26	Sector 27	Sector 28	Sector 29	Sector 30	Sector 31	Sector 34
Capital (ln)	0.383 ***	0.576 ***	0.472 ***	0.808 ***	0.326	0.223 ***	0.228 ***
	(0.0528)	(0.0478)	(0.0662)	(0.279)	(0.203)	(0.0680)	(0.0488)
Labor (ln)	0.731 ***	0.620 ***	0.707 ***	0.649	1.078 **	0.947 ***	0.925 ***
	(0.0963)	(0.0660)	(0.206)	(0.468)	(0.432)	(0.106)	(0.103)
Observations	740	1040	810	440	570	2445	930
Wald test statistic of constant returns to scale	3.370	57.84	1.351	4.571	3.010	5.093	5.511
Sargan–Hansen test statistic	3.50×10^{-8}	1.59×10^{-8}	2.28×10^{-8}	0.0780	1.65×10^{-8}	8.96×10^{-8}	4.04×10^{-9}

Note: standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$; Z-test statistics are in parenthesis; Wald test of constant returns to scale; proxy variables: raw material expenses. The test for the over-identifying restrictions is based on Sargan–Hansen's J-test. Manufacturing industry codes are presented in Table 1 (Column 1). Source: authors' estimation from VAES 2010–2015.

From Table 2, we do not find evidence of constant returns to scale in all sectors. Instead, most of them are characterized by increasing returns to scale.

Grounded on this estimated result shown in Table 2, the firm-level TFP was calculated using the command acfest in Stata for the analysis in Section 4.2. Table 3 presents the descriptive statistics of TFP. The highly performing sectors in terms of average productivity in 2010–2015 were wearing apparel (code 14), leather and related products (code 15), furniture (code 31), and the fabricated metal products sectors (code 25). The low-performing sectors were firms in chemicals and chemical products (code 20), electrical equipment (code 27), and food products (code 10).

Table 3. Total factor productivity (TFP) level by industries, 2010–2015.

Industry	Mean	Min	Max
10: Food products	4.994	−1.771	9.278
11: Beverages	2.935	−2.689	5.864
13: Textiles	5.329	0.721	9.323
14: Wearing apparel	7.890	2.236	11.760
15: Leather and related products	7.853	4.165	9.941
16: Wood and products of wood/cork	5.438	1.599	7.535
17: Paper and paper products	5.651	−1.692	8.535
18: Printing and reproduction of recorded media	6.262	2.889	8.702
20: Chemicals and chemical products	4.758	0.321	8.051
21: Pharmaceuticals, medicinal chemicals	6.050	2.486	10.166
22: Rubber and plastics products	5.800	0.150	8.765
23: Other non-metallic mineral products	5.304	−6.892	8.463
24: Basic metals	5.045	1.590	8.549
25: Fabricated metal products	6.397	1.120	9.419
26: Computer, electronic and optical products	6.407	2.670	9.921
27: Electrical equipment	4.827	0.981	6.734
28: Not-yet-classified machinery and equipment	5.501	1.196	7.876
29: Motor vehicles, trailers and semi-trailers	2.017	−1.302	3.702
30: Other transport equipment	5.309	−0.262	8.138
31: Furniture	6.901	1.572	9.853
34: Other manufacturing	7.056	−0.101	9.490
All manufacturing	5.921	−6.892	11.760

Source: authors' estimation from TFP regressions' results in Table 2, using the command acfest in Stata.

4.2. Determinants of TFP

Sample means and standard deviations of variables in the model of TFP determinants are presented in the Supplementary Materials, Table S1.

Table 4 presents the estimation results of the 21 manufacturing sectors. As indicated in the bottom line of Table 4, high levels of autocorrelation do not exist in most manufacturing sectors, as indicated by the second autocorrelation (AR(2)) Arellano-Bond test statistics, which are not significant at the 10% level, except for sector 10 (food products). In addition, Table 4 also ensures the validity of instrument variables since the Hansen J statistics in the bottom line are not significant at the 10% level in most manufacturing sectors, except for sectors 14 (wearing apparel), 27 (electrical equipment), and 31 (furniture).

Table 4. Determinants of TFP by industries, 2010–2015. VA: value-added.

VARIABLES	Sector 10	Sector 11	Sector 13	Sector 14	Sector 15	Sector 16	Sector 17
TFP, lagged	0.0668 *	0.174 **	0.0495	0.114 **	0.192 ***	-	0.234 ***
	(0.0395)	(0.0801)	(0.0460)	(0.0465)	(0.0572)	-	(0.0605)
Capital-to-labor ratio (ln), lagged	0.0130	−0.0443	−0.0171	0.0442 ***	0.0575 ***	−0.0099	0.0537 **
	(0.0174)	(0.0577)	(0.0257)	(0.0151)	(0.0171)	(0.0244)	(0.0267)
Workers (ln), lagged	−0.0983 **	−0.301 *	−0.125 **	0.0621	0.0349	−0.0108	−0.0298
	(0.0392)	(0.162)	(0.0624)	(0.0509)	(0.0794)	(0.0561)	(0.0935)
Wage (ln), lagged	0.0823 ***	0.189	0.106 *	−0.0588	−0.0347	0.0053	−0.0169
	(0.0317)	(0.121)	(0.0546)	(0.0442)	(0.0744)	(0.0540)	(0.0714)
Ages (ln), lagged	0.0200	−0.0024	−0.0318	0.0962 ***	−0.0238	−0.0333	−0.0506
	(0.0266)	(0.0993)	(0.0345)	(0.0216)	(0.0307)	(0.0426)	(0.0373)
VA per labor (ln), lagged						0.0831	
						(0.0576)	
Observations (Number of firms)	4835 (967)	480 (96)	2005 (401)	4425 (885)	1520 (304)	1820 (364)	1765 (353)
Hansen J statistic; Wald chi-squared statistic; AR(2) test statistic; Number of instruments	2.767; 104.8 ***; 2.720 ***; 12	5.624; 39.76 ***; 0.502; 18	13.45; 70.13 ***; 0.951; 18	17.51 **; 1237 ***; −0.0723; 18	5.545; 397.8 ***; −0.405; 18	5.042; 58.51 ***; −1.160; 16	10.29; 163.9 ***; 1.251; 16
VARIABLES	**Sector 18**	**Sector 20**	**Sector 21**	**Sector 22**	**Sector 23**	**Sector 24**	**Sector 25**
TFP, lagged	0.103	0.195 ***	0.0804	0.134 ***	0.0854	0.126 **	0.136 ***
	(0.0681)	(0.0514)	(0.122)	(0.0359)	(0.0524)	(0.0540)	(0.0390)
Capital to labor ratio (ln), lagged	−0.0104	0.0294	0.101	−0.0145	−0.0021	−0.0257	0.0379
	(0.0298)	(0.0286)	(0.106)	(0.0227)	(0.0188)	(0.0383)	(0.0276)
Workers (ln), lagged	−0.269 **	−0.0911	−0.429 ***	−0.200 ***	−0.151 **	−0.255 ***	0.153 ***
	(0.128)	(0.0574)	(0.166)	(0.0568)	(0.0594)	(0.0893)	(0.0563)
Wage (ln), lagged	0.131	0.0721	0.224 **	0.171 ***	0.100 **	0.232 ***	0.0873 *
	(0.0987)	(0.0477)	(0.112)	(0.0487)	(0.0470)	(0.0783)	(0.0521)
Ages (ln), lagged	0.0820 **	0.0011	−0.150 **	−0.0070	−0.0089	−0.0436	−0.0512
	(0.0363)	(0.0393)	(0.0645)	(0.0314)	(0.0269)	(0.0655)	(0.0314)
Observations (Number of firms)	965 (193)	1825 (365)	520 (104)	2755 (551)	3760 (752)	615 (123)	3350 (670)
Hansen J statistic; Wald chi-squared statistic; AR(2) test statistic; Number of instruments	9.724; 250 ***; 0.548; 18	5.354; 99.98 ***; 0.124; 16	6.609; 79.22 ***; 1.574; 16	12.16; 169.9 ***; 1.627; 18	8.246; 258.7 ***; 1.551; 18	6.510; 20.71 ***; −0.357; 18	10.20; 714.1 ***; 1.047; 18
VARIABLES	**Sector 26**	**Sector 27**	**Sector 28**	**Sector 29**	**Sector 30**	**Sector 31**	**Sector 34**
TFP, lagged	0.202 ***	0.210 ***	0.168 ***	0.314 ***	0.319 ***	0.0511	
	(0.0481)	(0.0574)	(0.0626)	(0.0617)	(0.0736)	(0.0405)	
Capital to labor ratio (ln), lagged	0.0254	−0.0397	−0.0487	−0.117 **	0.0427	−0.0232	0.0435
	(0.0352)	(0.0323)	(0.0364)	(0.0553)	(0.0444)	(0.0300)	(0.0329)
Workers (ln), lagged	−0.0584	−0.206 ***	−0.132 **	−0.262 ***	0.200 **	−0.0894 *	−0.0373
	(0.0719)	(0.0747)	(0.0652)	(0.0947)	(0.0899)	(0.0502)	(0.0847)
Wage (ln), lagged	0.0389	0.181 ***	0.188 ***	0.0710	−0.209 ***	0.0823 *	0.0082
	(0.0702)	(0.0652)	(0.0532)	(0.0781)	(0.0728)	(0.0458)	(0.0809)
Ages (ln), lagged	−0.0202	−0.0370	−0.101 *	0.0088	−0.126	−0.0220	0.0002
	(0.0604)	(0.0402)	(0.0592)	(0.0691)	(0.0918)	(0.0390)	(0.0671)
VA per labor (ln), lagged							0.171 **
							(0.0729)
Observations (Number of firms)	740 (148)	1035 (207)	805 (161)	440 (88)	565 (113)	2445 (489)	920 (184)
Hansen J statistic; Wald chi-squared statistic; AR(2) test statistic; Number of instruments	7.310; 120.7 ***; 0.602; 18	13.87 *; 60.47 ***; 0.748; 18	5.475; 229.5 ***; −0.0452; 16	4.191; 226 ***; 1.216; 18	8.514; 154.8 ***; 0.945; 18	17.52 **; 823.4 ***; −1.590; 18	11.52; 157.2 ***; −0.136; 18

Note: standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; manufacturing industry codes are presented in Table 1 (Column 1) or Table 3 (Column 1). Source: authors' estimation from VAES 2010–2015.

In Table 4, we observe that the estimated coefficients on lagged TFP are significantly positive at the common levels in most sectors, such as beverages (code 11), leather and related products (code 15), paper and paper products (code 17), chemicals and chemical products (code 20), rubber and plastics products (code 22), basic metals (code 24), fabricated metal products (code 25), computer, electronic and optical products (code 26), not-yet-classified machinery and equipment (code 28), motor vehicles, trailers and semi-trailers (code 29), and other transport equipment (code 30). Their magnitudes are from 0.13 to 0.32, which is relatively small, and these indicate a relatively quick adjustment of firm productivity over time in those sectors (cf. Kim et al. (2009) found a slow adjustment of firm productivity in the Japanese food sector over time). The significantly positive effects are found in every manufacturing sector if classified by, namely: low-tech manufacturing (such as beverages, leather and related products, and paper and paper products); medium low-tech manufacturing (such as fabricated metal products); medium high-tech manufacturing (such as motor vehicles, trailers and semi-trailers, and other transport equipment); and high-tech manufacturing (such as the computer, electronic and optical products) (see the classification in Kim (2018), and Harris and Moffat (2015)).

In Table 4, we observe that larger firms measured by the number of workers are less productive than smaller firms in sectors such as beverages (code 11), textiles (code 13), printing and reproduction of recorded media (code 18), pharmaceuticals and medicinal chemicals (code 21), rubber and plastics products (code 22), other non-metallic mineral products (code 23), basic metals (code 24), not-yet-classified machinery and equipment (code 28), and motor vehicles, trailers and semi-trailers (code 29). This finding is in line with Giang et al. (2019) and Giang et al. (2018) for Vietnamese manufacturing small and medium-sized enterprises (SMEs) in 2011–2015, Kreuser and Newman (2018) in South Africa, Fernandes (2008) in Bangladesh, and Söderbom and Teal (2004) in Ghana. Some studies that disaggregated the manufacturing sectors had similar results to ours. For example, the study of Satpathy et al. (2017) in India, which disaggregated into sectors like us, showed that significant positive effects of size are found in sectors such as agricultural and food products, textiles, basic metals, chemical and chemical products, electrical equipment, other transport equipment, pharmaceuticals and medicine, and rubber and plastic. Kim (2018) found that firm size has a positive influence on TFP growth in both low-tech and high-tech manufacturing sectors (at small, medium, and large scales), and a negative influence on both medium-low and medium-high tech manufacturing sectors (at small, medium and large scales) in Japan. However, we also find that larger firms are more productive than smaller firms in some sectors, namely fabricated metal products (code 25) and other transport equipment (code 30). In fact, the effect of firm size on productivity has been investigated intensively and the evidence is mixed. By contrast, Van Biesebroeck (2005) found that larger firms have higher productivity for several African countries.

We also find that older firms are generally more productive than younger ones in the printing and reproduction of recorded media sector (code 18). This is in line with Kreuser and Newman (2018) for the aggregated manufacturing sector in South Africa, and Xu et al. (2019) for the case of the Chinese furniture sector. However, our results also show negative effects in such sectors as pharmaceuticals and medicinal chemicals (code 21) and electrical equipment (code 27), and this is in line with the vintage effect or learning-by-doing effect as suggested by Jovanovic and Nyarko (1994), and the studies of Giang et al. (2019), and Giang et al. (2018) for Vietnamese manufacturing SMEs in 2011–2015.

Firms with higher capital–labor ratios are found to be more productive in some sectors, namely leather and related products (code 15) and paper and paper products (code 17), and this has also been found in Kreuser and Newman (2018) for the aggregated manufacturing sector in South Africa. However, a negative effect is found in motor vehicles, trailers, and semi-trailers (code 29).

Regarding labor quality measured by the average wage level, the higher the level of human capital is, the more productive the firm is. We find a positive association in sectors such as textiles (code 13), pharmaceuticals and medicinal chemicals (code 21), rubber and plastics products (code 22), other non-metallic mineral products (code 23), basic metals (code 24), fabricated metal products (code 25), and not-yet-classified machinery and equipment (code 28). However, a negative relationship between labor quality and productivity is evidenced in other transport equipment (code 30). Mixed evidence was recently also found in the manufacturing-disaggregated study by Kim (2018), who found that average wage has a negative influence on TFP growth in low-tech, medium-low, and medium-high tech manufacturing sectors, and positive one in high-tech manufacturing sectors in Japan.

The level of real value-added per worker of the firm is shown to be passively correlated with TFP only in other manufacturing sectors (code 34). This has also been found in Kreuser and Newman (2018) for the aggregated manufacturing sector in South Africa.

4.3. Heterogeneity of TFP

4.3.1. Labor Heterogeneity

Table 5 presents the estimation results of the 21 manufacturing sectors across heterogeneous groups in terms of employment size (full results are in Supplementary Materials, Table S2). Relevant tests in the bottom line of Table 5 include tests of high-level autocorrelation and the validity of instrument variables. Specifically, high levels of autocorrelation are not held in most manufacturing sectors as suggested by the AR (2) test statistics, which are not significant at the 10% level, except for food products (code 10—number of workers between 10–50, and 1000–5000), and other non-metallic mineral products (code 23—number of workers between 50–200).

Table 5. Labor-heterogeneity determinants of TFP by industries, 2010–2015.

VARIABLES	Workers						
	10–49	50–199	200–299	300–499	500–999	1000–4999	>5000
Sector 10: Food products (Number of observations: _1403)							
TFP, lagged	0.0465	−0.0397	0.0938	0.211 **	0.0590	0.337 ***	
Capital to labor ratio (ln), lagged	0.0227	−0.0062	0.0336	0.0814 **	0.0530	0.167 ***	
Workers (ln), lagged	−0.0010	−0.0603	0.0271	0.412 ***	−0.0181	−0.0054	
Wage (ln), lagged	0.0692	0.203 ***	0.212 **	−0.0417	0.0385	0.0514	
Ages (ln), lagged	0.0049	0.0086	0.0134	−0.0199	0.105 *	0.0505	
Sector 11: Beverages (Number of observations: _107)							
VA per labor (ln), lagged	0.270 **						
Capital to labor ratio (ln), lagged	−0.237 *	−0.106					
Workers (ln), lagged	−0.406	−0.537 *					
Wage (ln), lagged	0.125	0.454 **					
Sector 13: Textiles (Number of observations: _542)							
TFP, lagged	0.0018		0.297 **	0.130			
Workers (ln), lagged	−0.179 *	−0.0020	−0.0437	−0.180			
Wage (ln), lagged	0.185 **	0.142 *	0.185	0.308 **			
Ages (ln), lagged	−0.116 **	0.0125	0.0121	−0.0295			
Sector 14: Wearing apparel (Number of observations: _332)							
VA per labor (ln), lagged	0.209	0.0572		0.0982	0.225 ***		
Capital to labor ratio (ln), lagged	0.0838	0.0860 ***	0.0228	0.105 ***	0.0338	0.0485	0.120
Workers (ln), lagged	0.175	0.146	0.254 **	0.486 ***	0.335 ***	0.134	−0.141
Wage (ln), lagged	−0.0050 (0.179)	0.106	0.136	−0.168 *	−0.188 ***	−0.0986	0.302 **
Ages (ln), lagged	0.0843	0.0103	0.117 **	0.0787	0.0995 **	0.100 ***	0.0037
TFP, lagged			0.0770			0.163	−0.216
Sector 15: Leather and related products (Number of observations: _92)							
TFP, lagged	0.566 **	0.172	0.167		−0.0011		
Capital to labor ratio (ln), lagged	0.0876	0.0590	0.0682 *	0.0439	0.120 **	0.0109	0.0673
Workers (ln), lagged	0.615 **	0.119	0.188	−0.0628	0.262	0.190 *	−0.0556
Wage (ln), lagged	−0.386 **	0.0399	0.205	0.352 **	0.0526	−0.122	0.0141
Ages (ln), lagged	−0.116	−0.111 *	−0.121 *	0.0205	0.0371	−0.0291	0.0737
VA per labor (ln), lagged				−0.0187		0.161 **	0.134
Sector 16: Wood and products of wood/cork (Number of observations: _733)							
TFP, lagged	0.0808	0.254 ***	0.360 *				
Capital to labor ratio (ln), lagged	0.0460	0.0544 *	0.0804				
Workers (ln), lagged	0.128	0.241 **	0.456 **				
Sector 17: Paper and paper products (Number of observations: _630)							
TFP, lagged	0.208 **	0.188 *	0.347 ***	0.392 ***			
Capital to labor ratio (ln), lagged	0.0429	0.0145	0.214 ***	0.192 ***			
Workers (ln), lagged	0.0705	0.0527	0.384 **	0.329			
Wage (ln), lagged	0.0699	0.0416	−0.0996	−0.275 *			
Ages (ln), lagged	−0.0466	−0.0548	−0.167 **	0.153 *			
Sector 18: Printing and reproduction of recorded media (Number of observations: _472)							
VA (ln), lagged	0.194 **	0.0975					
Workers (ln), lagged	−0.166	−0.279 **					
Wage (ln), lagged	0.0455	0.198 **					
Sector 20: Chemicals and chemical products (Number of observations: _779)							
TFP, lagged	0.271 ***		0.334 *	0.0715			
Capital to labor ratio (ln), lagged	0.0704	−0.0777	−0.0063	0.0550	−0.282 **		
VA per labor (ln), lagged		0.147 *			0.450 ***		
Sector 21: Pharmaceuticals, medicinal chemicals (Number of observations: _208)							
Ages (ln), lagged	−0.210 **	−0.0928					
VA per labor (ln), lagged		0.340 **					
Sector 22: Rubber and plastics products (Number of observations: _737)							
VA per labor (ln), lagged	0.0901	0.114 **					
Capital to labor ratio (ln), lagged	−0.142 ***	−0.0257	0.0403	0.0889	0.0706		
Workers (ln), lagged	−0.289 **	−0.0764	−0.0199	−0.0010	−0.159		
Wage (ln), lagged	0.317 ***	0.160 ***	0.302 ***	−0.108	0.0174		
Ages (ln), lagged	−0.0576	−0.0809	−0.0062	−0.0340	0.0222		
TFP, lagged			0.187 * (0.110)	0.256 *** (0.0899)	0.0380 (0.271)		
Sector 23: Other non-metallic mineral products (Number of observations: _986)							
VA per labor (ln), lagged	0.0947		0.0200				
Capital to labor ratio (ln), lagged	−0.0592	0.0222	0.0454	0.0336	0.179 ***		
Workers (ln), lagged	−0.0914	0.0062	0.126	0.303 *	0.337 **		
Wage (ln), lagged	0.115 *	0.111	0.293 **	0.0108	−0.0114		
Ages (ln), lagged	−0.135 **	0.104 ***	0.0690	−0.0864	−0.0331		
TFP, lagged		0.139 *		0.219 **	0.171		
Sector 24: Basic metals (Number of observations: _243)							
VA per labor (ln), lagged	0.184						
Capital to labor ratio (ln), lagged	−0.0893	−0.0187					
Workers (ln), lagged	−0.213	0.216					
Wage (ln), lagged	0.238	0.162 (0.146)					
Ages (ln), lagged	−0.0415	−0.285 *					
TFP, lagged		0.115					

Table 5. *Cont.*

VARIABLES	Workers						
	10–49	**50–199**	**200–299**	**300–499**	**500–999**	**1000–4999**	**>5000**
Sector 25: Fabricated metal products (Number of observations: _1492)							
TFP, lagged	0.248 ***	0.147 *	0.218		−0.0666		
Capital to labor ratio (ln), lagged	0.118 **	0.0069	0.0168	−0.0768	0.0413		
Workers (ln), lagged	0.375 ***	0.0772	0.0972	0.137	0.210 *		
Wage (ln), lagged	−0.0431	0.144 *	0.0251	−0.0452	0.0257 (0.108)		
Sector 26: Computer, electronic and optical products (Number of observations: _217)							
TFP, lagged	0.338 ***	0.280 ***	0.108	0.135			
Wage (ln), lagged	−0.194	−0.173	0.285 **	0.0049			
Sector 27: Electrical equipment (Number of observations: _235)							
TFP, lagged	0.173 **	0.175 **	0.525 ***				
Capital to labor ratio (ln), lagged	−0.111	−0.0206	0.0193	−0.267 **			
Workers (ln), lagged	−0.423 **	−0.227 **	0.296 * (0.161)	0.0439			
Wage (ln), lagged	0.373 ***	0.254 ***	−0.104 (0.123)	−0.0420			
Ages (ln), lagged	−0.283 **	−0.0403	0.0891	0.100			
VA per labor (ln), lagged				0.343 ***			
Sector 28: Not-yet-classified machinery and equipment (Number of observations: _364)							
TFP, lagged	0.0686	0.266 *					
Wage (ln), lagged	0.228 ***	0.152					
Ages (ln), lagged	0.128 (0.0848)	−0.0236 (0.0753)					
Sector 30: Other transport equipment (N = _113)							
VA per labor (ln), lagged		0.184 ** (0.0821)					
Sector 31: Furniture (Number of observations: _403)							
TFP, lagged	−0.208	0.0807	0.0056	0.0240	0.268 ***	0.0736	
Capital to labor ratio (ln), lagged	0.0306	−0.0441 *	−0.0657	0.0964 **	0.0618	−0.0805	
Workers (ln), lagged	−0.0107	−0.0031	−0.0089	−0.0256	0.254 **	0.219	
Wage (ln), lagged	0.177	0.174 **	0.298 ***	0.220 ***	−0.0457	−0.0548	
Ages (ln), lagged	−0.156 *	−0.0551	−0.0138	0.0752	0.165	−0.169 **	
Sector 34: Other manufacturing sectors (Number of observations: _175)							
TFP, lagged	0.0477	0.0391	0.146	0.227	0.330 ***		
Capital to labor ratio (ln), lagged	0.0324	0.108 **	0.0704	−0.00101	0.0771	0.0814	
Wage (ln), lagged	0.119	0.183 *	0.360 *	−0.218	0.0206	−0.218 **	
VA per labor (ln), lagged						0.322 *** (0.0788)	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; source: authors' estimation from VAES 2010–2015.

On top of that, the validity of instrument variables based on Hansen J statistics is observed in most manufacturing sectors, except for wearing apparel (code 14—number of workers between 10–200, 300–500, and 1000–5000), wood and products of wood/cork (code 16—number of workers between 10–200), paper and paper products (code 17—laborers between 10–200). The excluding list is continued with chemicals and chemical products (code 20—number of workers between 200–300, and 500–1000), rubber and plastics products (code 22—number of workers between 10–50, and 200–300), other non-metallic mineral products (code 23—number of workers between 10–200), fabricated metal products (code 25—number of workers between 10–50, and between 200–300), furniture (code 31—number of workers between 10–50, and 1000–5000), and other manufacturing sectors (code 34—number of workers between 10–50).

In the following part, we discuss the significant findings. Table 5 shows that firms' size is statistically significantly positive in food products (code 10—number of workers between 300–500), wearing apparel (code 14—number of workers between 200–1000), leather and related products (code 15—number of workers between 10–50 and between 1000–5000), wood and products of wood/cork (code 16—number of workers between 200–300), paper and paper products (code 17—laborers between 200–300), and furniture (code 31—number of workers between 500–1000). Besides, two sectors belonged to medium low-tech manufacturing, showing statistically significant positive effects in (1) other non-metallic mineral products (code 23—number of workers between 300–500 and between 500–5000); and (2) fabricated metal products (code 25—number of workers between 500–1000). Moreover, the sector of electrical equipment (code 27) that belonged to medium high-tech manufacturing has evidence of a statistically significant positive effect for firms with number of workers between

200–300. Similar results can also be found in Kreuser and Newman (2018), although these authors conducted their research for the aggregated manufacturing sector in South Africa and the classification of a firm's size by number workers is not the same with us. Productivity heterogeneity in labor was discovered in Kim (2018), who found that large firms are associated with higher productivity in low-technology, medium-low-technology, and medium-high-technology manufacturing sectors, but with lower productivity in the high-technology manufacturing sector.

A statistically negative effect of a firm's size is observed in printing and reproduction of recorded media (code 18—number of workers between 50–200), which belongs to the low-tech manufacturing sector, and in electrical equipment (code 27—number of workers between 10–50 and 50–200), which belongs to the medium high-tech manufacturing sector. Giang et al. (2018) found a negative effect in the sector of metal and machinery products for Vietnamese manufacturing SMEs in 2011–2015.

Regarding labor quality measured by average wage, Table 5 shows that firms' average wage is statistically significantly positive in food products (code 10—number of workers between 50–300), beverages (code 11—number of workers between 50–200), textiles (code 13—number of workers between 10–200 and 300–500), wearing apparel (code 14—number of workers more than 5000), leather and related products (code 15—number of workers between 10–50), printing and reproduction of recorded media (code 18—number of workers between 50–200), and furniture (code 31—number of workers between 200–500). All of the sectors above belong to the low-tech manufacturing sector. Besides, regarding the medium low-tech manufacturing sectors, the firms' size is statistically significantly positive in other non-metallic mineral products (code 23—number of workers between 200–300), and fabricated metal products (code 25—number of workers between 50–200). Besides, concerning the medium high-tech manufacturing sector, the firms' size is statistically significantly positive in electrical equipment (code 27—number of workers between 10–200), not-yet-classified machinery and equipment (code 28—number of workers between 10–50). In relation to the high-tech manufacturing sector, the firms' size is statistically significantly positive in the computer, electronic and optical products (code 26—number of workers between 200–300). Productivity heterogeneity in labor quality has been discovered in Kim (2018), who has found that lower-wage level is associated with lower productivity in low-technology, medium-low-technology, medium-high-technology, and high-technology manufacturing sectors in Japan.

A statistically negative effect of labor quality is observed in low-tech manufacturing sectors such as leather and related products (code 15—number of workers between 300–500), and paper and paper products (code 17—number of workers between 300–500).

With respect to firms' age, Table 5 shows that the firms' age is statistically significantly positive in food products (code 10—number of workers between 500–1000), wearing apparel (code 14—number of workers between 200–300, and 500–1000), and paper and paper products (code 17—number of workers between 300–500). Only one sector belonged to medium low-tech manufacturing sectors, namely other non-metallic mineral products (code 23—number of workers between 50–200), and basic metals (code 24—number of workers between 50–200), the signals are statistically significantly positive effects. That is in line with Xu et al. (2019) for the case of the Chinese furniture sector. However, the statistically negative effect is observed in textiles (code 13—with workers between 10–50), leather and related products (code 15—number of workers between 50–300), paper and paper products (code 17—number of workers between 50–300). That being said, all have belonged to the low-tech manufacturing sector. In addition, the medium high-tech manufacturing sectors such as electrical equipment (code 27—number of workers between 10–50) also accompanies a statistically negative effect. Besides, the high-tech manufacturing sector, namely pharmaceuticals, medicinal chemicals (code 21—number of workers between 10–50) shows a statistically negative effect.

With reference to the firms' lagged total factor productivity, Table 5 shows that the firms' lagged total factor productivity is statistically significantly positive in food products (code 10—number of workers between 300–500), textiles (code 13—number of workers between 200–300), leather and related products (code 15—number of workers between 10–50), paper and paper products (code 17—number of workers between 200–500), furniture (code 31—number of workers between 500–1000). Besides, about medium low-tech manufacturing sectors, namely rubber and plastics products (code 22—number of workers between 300–500), other non-metallic mineral products (code 23—number of workers between 50–200, and 300–500), and fabricated metal products (code 25—number of workers between 50–200), there exist a statistically significantly positive effect. On top of that, medium high-tech manufacturing sectors such as chemicals and chemical products (code 20—number of workers between 10–50), electrical equipment (code 27—number of workers between 10–300), and not-yet-classified machinery and equipment (code 28—number of workers between 50–200) also go in line with a statistically significantly positive effect. Besides, the high-tech manufacturing sector, namely computer, electronic, and optical products (code 26—number of workers between 10–200) obtains a statistically positive effect.

In relation to firms' capital-to-labor ratio, Table 5 shows that the firms' capital intensity is statistically significantly positive in food products (code 10—number of workers between 300–500, and 1000–5000), wearing apparel (code 14—number of workers 50–200, and 300–500), leather and related products (code 15—number of workers between 200–300, and 500–1000), wood and products of wood/cork (code 16—number of workers between 50–200), paper and paper products (code 17—number of workers between 200–500); and furniture (code 31—number of workers between 300–500). Two sectors belonged to medium low-tech manufacturing sectors, namely other non-metallic mineral products (code 23—number of workers between 500–1000), and fabricated metal products (code 25—number of workers between 10–50) show significantly positive effects. However, a statistically negative effect of the firms' capital intensity is observed in beverages (code 11—number of workers between 10–50), and rubber and plastics products (code 22—number of workers between 10–50). Medium high-tech manufacturing sectors, including chemicals and chemical products (code 20—number of workers between 500–1000), and electrical equipment (code 27—number of workers between 300–500) are found with statistically negative effects.

The level of real value-added per worker of the firms is shown to be passively correlated with TFP only in beverages (code 11—number of workers between 10–50); in wearing apparel (code 14—number of workers between 500–1000); in leather and related products (code 15—number of workers between 1000–5000); and in rubber and plastics products (code 22—number of workers between 50–200). With respect to medium high-tech manufacturing sectors, three sectors, namely chemicals and chemical products (code 20—number of workers between 50–200), electrical equipment (code 27—number of workers between 300–500), and other transport equipment (code 30—number of workers between 50–200) are also accompanied by a negative relationship.

4.3.2. Capital Stock Heterogeneity

Table 6 presents the estimation results of the 21 manufacturing sectors across groups of fixed capital (full results are in the Supplementary Materials, Table S3). Similar tests in were conducted Sections 4.2 and 4.3.1 to examine the existence of high levels of autocorrelation and the validity of instrument variables. The results in Table 6 indicate that the first problem does not hold in most manufacturing sectors, except for food products (code 10—fixed capital between 200–500 Vietnamese Dong (VND) billion), leather and related products (code 15—fixed capital between 10–50 VND billion), wood and products of wood/cork (code 16—fixed capital less than 10 VND billion), and other non-metallic mineral products (code 23—fixed capital less than 10 VND billion).

In addition, the second problem is solved in most manufacturing industries, except for wearing apparel (code 14—fixed capital less than 50 VND billion), leather and related products (code 15—fixed capital between 10–50 VND billion), wood and products of wood/cork (code 16—fixed capital less than 50 VND billion and between 200–500 VND billion), and printing and reproduction of recorded media (code 18—fixed capital between 50–200 VND billion). The list also includes some more sectors, such as chemicals and chemical products (code 20—fixed capital less than 10 VND billion), pharmaceuticals and medicinal chemicals (code 21—fixed capital less than 10 VND billion), rubber and plastics products (code 22—fixed capital between 50–500 VND billion), other non-metallic mineral products (code 23—fixed capital less than 10 VND billion), fabricated metal products (code 25—fixed capital less than 10 VND billion), and computer, electronic and optical products (code 26—fixed capital between 50–200 VND billion).

Table 6. Capital-heterogeneity determinants of TFP by industries, 2010–2015.

VARIABLES	Total Fixed Capital				
	<10 VND Billion	**From 10 to Less than 50 VND Billion**	**From 50 to Less than 200 VND Billion**	**From 200 to Less than 500 VND Billion**	**>500 VND Billion**
Sector 10: Food products (Number of observations: _838)					
Capital to labor ratio (ln), lagged	−0.0345	0.0543	0.0462	0.0305	0.280 ***
Workers (ln), lagged	−0.127	−0.0121	0.0512	−0.318 ***	−0.0038
Wage (ln), lagged	0.225 ***	0.0958 **	0.0453	0.237 **	0.0193
TFP, lagged			0.109 *		0.167
Sector 11: Beverages Number of observations: _87)					
TFP, lagged	0.320 ***		0.516 ***		
Workers (ln), lagged	0.0387	−0.598 **	0.0005		
Wage (ln), lagged	0.153	0.479 **	0.0278		
Sector 13: Textiles (Number of observations: _461)					
VA per labor (ln), lagged	−0.0873				
Capital to labor ratio (ln), lagged	−0.121 **	0.0357	0.0613	−0.0890	0.0921 *
Workers (ln), lagged	−0.428 ***	−0.0487	0.132	−0.240	−0.0838
Wage (ln), lagged	0.411 ***	0.0713	−0.0171	0.157	0.0496
TFP, lagged		0.100	0.147 **	0.0231	0.174 *
Sector 14: Wearing apparel (Number of observations: _1016)					
TFP, lagged	−0.179 *				0.0224
Capital to labor ratio (ln), lagged	0.0450	−3.33e−06	0.0580 *	0.0538	0.187 **
Workers (ln), lagged	−0.223 *	0.0904	−0.0606	0.335 *	0.0394
Wage (ln), lagged	0.322 ***	−0.133 **	−0.0304	−0.428 ***	−0.105
Ages (ln), lagged	0.0553	0.0977 ***	0.0488	0.123 ***	0.130 *
VA per labor (ln), lagged		0.133 *	0.184 ***	0.385 ***	
Sector 15: Leather and related products (Number of observations: _249)					
TFP, lagged	0.0372	0.315 ***	0.101	−0.0387	
Capital to labor ratio (ln), lagged	0.0521	0.0469	0.0940	−0.0917	0.235 **
Workers (ln), lagged	−0.0628	−0.0140	0.202 *	−0.344 **	−0.165 *
Wage (ln), lagged	0.110	0.0423	−0.154 *	0.163	0.120
Sector 16: Wood and products of wood/cork (Number of observations: _604)					
TFP, lagged		0.174 **	0.145	0.381	
Sector 17: Paper and paper products (Number of observations: _224)					
TFP, lagged	0.364		0.305 **	0.530 ***	0.0651
Capital to labor ratio (ln), lagged	0.0113	0.0541	0.153 **	0.325 **	0.424 **
Workers (ln), lagged	0.178	−0.175 *	0.265	0.160	−0.0413
Ages (ln), lagged	−0.0046	0.0460	−0.187 **	−0.0568	0.125
Sector 18: Printing and reproduction of recorded media (Number of observations: _379)					
TFP, lagged	0.0957	0.126 *			
Capital to labor ratio (ln), lagged	−0.0270	−0.0927	−0.0862		
Workers (ln), lagged	−0.305 *	−0.433 ***	−0.440 *		
Wage (ln), lagged	0.169	0.228 **	−0.0076		
Ages (ln), lagged	0.0781 *	0.107 *	−0.0300		
Value-added per labor (ln), lagged			0.454 *		
Sector 20: Chemicals and chemical products (Number of observations: _209)					
TFP, lagged	−0.0071	0.239 ***		0.397 ***	−0.0125
Workers (ln), lagged	−0.121	0.0031	−0.0456	−0.0098	−0.291 **
Ages (ln), lagged	0.210 *	−0.108	−0.0095	−0.0305	0.0043
VA per labor (ln), lagged			0.312 ***		
Sector 21: Pharmaceuticals, medicinal chemicals (Number of observations: _85)					
TFP, lagged	−0.229	0.339 **			
Capital to labor ratio (ln), lagged	0.0884	0.0061	0.299 **		
Workers (ln), lagged	−0.782	−0.274	−0.550 ***		
Wage (ln), lagged	0.784 **	0.0700	0.224 *		
Ages (ln), lagged	−0.154	−0.0488	−0.271 ***		
VA per labor (ln), lagged			−0.203 *		
Sector 22: Rubber and plastics products (Number of observations: _228)					
VA per labor (ln), lagged	0.126		0.138 *		
Capital to labor ratio (ln), lagged	−0.139 ***	−0.0984 **	0.0201	0.0586	0.180 *
Workers (ln), lagged	−0.190	−0.247 ** (0.0964)	−0.0987	−0.221	−0.409 **
Wage (ln), lagged	0.219	0.229 ***	0.0775	0.0850	0.305 **
Ages (ln), lagged	0.0941	−0.130 **	−0.0239	−0.0570	0.0618
TFP, lagged		0.0776		0.145	0.162 *

Table 6. *Cont.*

VARIABLES	Total Fixed Capital				
	<10 VND Billion	From 10 to Less than 50 VND Billion	From 50 to Less than 200 VND Billion	From 200 to Less than 500 VND Billion	>500 VND Billion
Sector 23: Other non-metallic mineral products (Number of observations: _696)					
TFP, lagged	0.0469		0.181	0.127	0.166 *
Capital to labor ratio (ln), lagged	0.0784 *	−0.108 **	0.0993 *	−0.0112	0.159 **
Workers (ln), lagged	0.0403	−0.255 ***	0.0336	−0.365	−0.0653
Wage (ln), lagged	0.0811	0.130 **	0.0270	0.104	0.0451
Ages (ln), lagged	−0.0444	0.0701 **	0.0068	−0.0997	−0.164 ***
Sector 24: Basic metals (Number of observations: _185)					
Ages (ln), lagged	−0.123	−0.294 *			
TFP, lagged		0.209 *			
Sector 25: Fabricated metal products (Number of observations: _657)					
TFP, lagged	0.182		0.128 *		0.272 **
Capital to labor ratio (ln), lagged	−0.0698	0.0530	0.142 **	0.0153	0.202 *
Workers (ln), lagged	0.0767	0.339 ***	0.270 ***	0.120	0.125
Ages (ln), lagged	−0.0212	−0.0952 **	−0.0304	−0.119	−0.0617
VA per labor (log), lagged		0.178 ***		0.0403	
Sector 26: Computer, electronic and optical products (Number of observations: _134)					
TFP, lagged	0.165	0.111		0.169 **	
Capital to labor ratio (ln), lagged	0.0095	0.0943	0.0374	0.188 **	
Sector 27: Electrical equipment (Number of observations: _324)					
Workers (ln), lagged	−0.291 **	−0.164	−0.235 *	−0.0389	
Wage (ln), lagged	0.327 ***	0.166	0.158 *	−0.0024	
TFP, lagged		0.245 **	0.243 ***	0.226 **	
Sector 28: Not-yet-classified machinery and equipment (Number of observations: _161)					
TFP, lagged	−0.0682		0.272 *	0.132	
Capital to labor ratio (ln), lagged	0.0359	−0.0540	−0.283 **	−0.0355	
Workers (ln), lagged	−0.317 *	−0.131	−0.391	−0.117	
Wage (ln), lagged	0.533 ***	0.244 ***	0.387	0.0971 *	
Ages (ln), lagged	0.141 *	−0.0101	−0.120	−0.189	
Sector 29: Motor vehicles, trailers and semi-trailers (Number of observations: _93)					
TFP, lagged	0.201 **	0.303 **	0.395 **	0.148	
Capital to labor ratio (ln), lagged	−0.0708	−0.139	−0.370 **	0.106	
Workers (ln), lagged	−0.237	−0.123	−0.210	−0.518 **	
Wage (ln), lagged	0.156	0.0344	−0.0497	0.366 **	
Sector 30: Other transport equipment (Number of observations: _137)					
VA per labor (ln), lagged	0.299	0.307 ***			
Capital to labor ratio (ln), lagged	0.0386	−0.0775	0.149	0.290 **	
Wage (ln), lagged	−0.143	−0.232 *	−0.207	−0.0896	
TFP, lagged			0.360 *** (0.127)	0.243 * (0.129)	
Sector 34: Other manufacturing sectors (Number of observations: _167)					
TFP, lagged	0.0356	0.0551	0.220 **		
Capital to labor ratio (ln), lagged	0.137	−0.145 *	−0.177 *	−0.203	
Workers (ln), lagged	0.0250	−0.361 ***	−0.367 ***	0.108	
Wage (ln), lagged	0.145	0.164 *	0.121 *	−0.526 **	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: Authors' estimation from VAES 2010–2015.

In the following part, we discuss the significant findings. Table 6 shows that firms' size is statistically significantly positive in wearing apparel (code 14—fixed capital between 200–500 VND billion), leather and related products (code 15—fixed capital between 50–200 VND billion), and fabricated metal products (code 25—fixed capital between 10–200 VND billion). However, the statistically negative effect is observed in beverages (code 11—fixed capital between 10–50 VND billion), textiles (code 13—fixed capital less than 10 VND billion), leather and related (code 15—fixed capital larger than 200 VND billion), paper and paper products (code 17—fixed capital between 10–50 VND billion), printing and reproduction of recorded media (code 18—fixed capital up to 50 VND billion), and rubber and plastics products (code 22—fixed capital between 50–200 VND billion and larger than 500 VND billion). In terms of the medium low-tech manufacturing sector, other non-metallic mineral products (code 23—fixed capital between 10–50 VND billion) also show a significant negative effect. Besides, the medium high-tech manufacturing sectors chemicals and chemical products (code 20—fixed capital larger than 500 VND billion), electrical equipment (code 27—fixed capital less than 10 VND billion and in the range 50–200 VND billion), not-yet-classified machinery and equipment (code 28—fixed capital less than 10 VND billion), and motor vehicles, trailers and semi-trailers (code 29—fixed capital between 200–500 VND billion) are in line with a significantly negative correlation. Moreover, the high-tech manufacturing sector, namely pharmaceuticals and medicinal chemicals (code 21—fixed capital between 50–200 VND billion), obtains a statistically negative effect.

As for labor quality measured by average wage, Table 6 shows that firms' size is statistically significantly positive in food products (code 10—fixed capital up to 50 VND billion), beverages (code 11—fixed capital between 10–50 VND billion), textiles (code 13—fixed capital up to 10 VND billion), printing and reproduction of recorded media (code 18—fixed capital between 10–50 VND billion), and rubber and plastics products (code 22—fixed capital between 10–50 VND billion and larger than 500 VND billion). In terms of medium high-tech manufacturing sectors, electrical equipment (code 27—fixed capital less than 10 VND billion and between 50–200 VND billion), not-yet-classified machinery and equipment (code 28—fixed capital less than 50 VND billion and between 200–500 VND billion), and motor vehicles, trailers and semi-trailers (code 29—fixed capital between 200–500 VND billion) also have a significantly positive effect. In addition, the high-tech manufacturing sector, namely pharmaceuticals and medicinal chemicals (code 21—fixed capital between 50–200 VND billion) obtains a significantly positive effect. However, a statistically negative effect is observed in wearing apparel (code 14—fixed capital between 200–500 VND billion) and leather and related products (code 15—fixed capital between 10–50 VND billion). Moreover, in terms of the medium low-tech manufacturing sector, other non-metallic mineral products (code 23—fixed capital between 10–50 VND billion), and in terms of medium high-tech manufacturing sector, other transport equipment (code 30—fixed capital between 10–50 VND billion), are associated with statistically negative effects.

With regard to firms' age, Table 6 shows that firms' age is statistically significantly positive in wearing apparel (code 14—fixed capital larger than 200 VND billion) and printing and reproduction of recorded media (code 18—fixed capital between 10–50 VND billion). In addition, other non-metallic mineral products (code 23—fixed capital between 10–50 VND billion), which belong to the medium low-tech manufacturing sector, and not-yet-classified machinery and equipment (code 28—fixed capital less than 10 VND billion), which belong to the high-tech manufacturing sector, are also affiliated with significantly positive effects. However, a statistically negative effect is observed in leather and related products (code 15—fixed capital between 50–200 VND billion) and rubber and plastics products (code 22—fixed capital between 10–50 VND billion). The negative signs are also found in the medium low-tech manufacturing sectors, such as other non-metallic mineral products (code 23—fixed capital more than 500 VND billion), basic metals (code 24—fixed capital between 10–50 VND billion), and fabricated metal products (code 25—fixed capital between 10–50 VND billion). Only one high-tech manufacturing sector, namely pharmaceuticals and medicinal chemicals (code 21—fixed capital between 50–200 VND billion) observes a statistically negative effect.

Regarding firms' lagged total factor productivity, Table 6 shows that the firms' lagged total factor productivity is statistically significantly positive in food products (code 10—fixed capital between 50–200 VND billion), beverages (code 11—fixed capital less than 10 VND billion and in the range 50–200 VND billion), textiles (code 13—fixed capital between 50–200 VND billion and larger than 500 VND billion), and paper and paper products (code 17—fixed capital between 50–200 VND billion). The list further includes printing and reproduction of recorded media (code 18—fixed capital between 10–50 VND billion), rubber and plastics products (code 22—fixed capital larger than 500 VND billion), and fabricated metal products (code 25—fixed capital between 50–200 VND billion and more than 500 VND billion). In addition, two medium low-tech manufacturing sectors, including other non-metallic mineral products (code 23—fixed capital larger than 500 VND billion) and basic metals (code 24—fixed capital between 10–50 VND billion) have significantly positive effects. Moreover, several medium high-tech manufacturing sectors, such as chemicals and chemical products (code 20—fixed capital between 10–50 VND billion and between 200–500 VND billion), electrical equipment (code 27—fixed capital between 10–500 VND billion), not-yet-classified machinery and equipment (code 28—fixed capital between 50–200 VND billion), motor vehicles, trailers and semi-trailers (code

29—fixed capital up to 200 VND billion), and other transport equipment (code 30—fixed capital between 200–500 VND billion) are also observed with significantly positive effects. Besides, two high-tech manufacturing sectors, namely pharmaceuticals and medicinal chemicals (code 21—fixed capital between 10–50 VND billion), and computer, electronic and optical products (code 26—fixed capital between 200–500 VND billion) indicate the existence of significantly positive effects.

With regards to firms' capital-to-labor ratio, Table 6 shows that the firms' capital intensity is statistically significantly positive in food products (code 10—fixed capital larger than 500 VND billion), textiles (code 13—fixed capital larger than 500 VND billion), and wearing apparel (code 14—fixed capital between 50–200 VND billion and larger than 500 VND billion). Others include leather and related products (code 15—fixed capital larger than 500 VND billion), paper and paper products (code 17—fixed capital between 50–200 VND billion and larger than 500 VND billion), and fabricated metal products (code 25—fixed capital between 50–200 VND billion and larger than 500 VND billion). Moreover, two medium low-tech manufacturing sectors, including rubber and plastics products (code 22—fixed capital larger than 500 VND billion) and other non-metallic mineral products (code 23—fixed capital between 50–200 VND billion and for larger than 500 VND billion), show significantly positive effects. Besides, two high-tech manufacturing sectors, namely pharmaceuticals and medicinal chemicals (code 21—fixed capital between 50–200 VND billion) and computer, electronic and optical products (code 26—fixed capital between 200–500 VND billion) show significantly positive impacts. Last but not least, one medium high-tech manufacturing sector, namely other transport equipment (code 30—fixed capital between 200–500 VND billion) also shows a significantly positive impact. However, the statistically negative effect of the firms' capital intensity is observed in low-tech manufacturing sectors, such as textiles (code 13—fixed capital less than 10 VND billion) and rubber and plastics products (code 22—fixed capital up to 50 VND billion); and in the medium low-tech manufacturing sectors, such as other non-metallic mineral products (code 23—fixed capital between 10–50 VND billion). The list includes the medium high-tech manufacturing sectors, namely not-yet-classified machinery and equipment (code 28—fixed capital in the range 50–200 VND billion) and motor vehicles, trailers and semi-trailers (code 29—fixed capital in the range 50–200 VND billion). Productivity heterogeneity in the capital has also been discovered in Kim (2018), who found that higher capital intensity is associated with lower productivity in the medium-low-technology and high-technology manufacturing sectors in Japan.

The level of real value-added per worker of firms is shown to be positively correlated with TFP only in wearing apparel (code 14—fixed capital between 50–500 VND billion) and fabricated metal products (code 25—fixed capital between 10–50 VND billion), and in two medium high-tech manufacturing sectors, including chemicals and chemical products (code 20—fixed capital between 50–200 VND billion), and other transport equipment (code 30—fixed capital between 10–50 VND billion). However, a statistically negative effect of the firms' capital intensity is observed in pharmaceuticals and medicinal chemicals (code 21—fixed capital between 50–200 VND billion).

5. Conclusions and Implications

Several challenges remain for researchers to understand differences in total factor productivity, namely: (1) empirical difficulties in the measurement of TFP levels; (2) model uncertainty on key determinants; and (3) heterogeneity between manufacturing sectors and heterogeneity within manufacturing sectors in terms of labor and capital that have been increasing reconsidered recently. This paper, using Vietnamese firm-level data for the period 2010–2015, applied the method of Ackerberg et al. (2006), which is an extension of the technique by Levinsohn and Petrin (2003), which has been employed to measure TFP, and the generalized method of moments, which has been used to identify factors that affect differences in the level of productivity across manufacturing subsectors and clarify the heterogeneous determinants of TFP within sectors. To the best of our knowledge, this study is the first to examine the heterogeneity of determinants of firm-level TFP in Vietnam and in a transitional country as well using GMM technique. The current paper is also the first attempt to explore the issue of economic growth in terms of manufacturing sectors within a specific country. Our estimations, in general, show that large firms have significantly greater TFP levels than small firms in some fragmentations of firms in terms of both labor and total capital and in some manufacturing sectors. To be more specific:

First, regarding labor heterogeneity, our estimations show that large firms in terms of labor have significantly greater TFP levels than small firms in some fragmentations of a firm's labor size and in some manufacturing sectors, as indicated in previous studies. However, the results also confirm the recent finding that a statistically negative effect of a firm's size exists. The studies also found that labor quality has a positive effect on the productivity in some manufacturing sectors. In addition, our study may be the first in discovering that the negative effect of labor quality exists in certain low-tech manufacturing sectors and at certain levels of labor, namely: leather and related products (code 15) and paper and paper products (code 17), both with workers in the range of 300–500 workers. Regarding the firms' ages, the results also confirm both the vintage effects and the learning-by-doing effects existing in certain manufacturing sectors, and that contributes to the mixture pictures of empirical studies so far. As for the firms' productivity adjustment, the significant positive effects of lagged total factor productivity confirm a relatively quick adjustment over time in certain sectors, as found in some previous studies. Last but not least, our results found both significantly positive and significantly negative effects of firms' capital intensity level (measured by capital-to-labor ratio) in certain sectors and a purely negative effect of labor productivity in the low-tech manufacturing and medium high-tech manufacturing sectors.

Second, with respect to capital heterogeneity, our results may be the first to find that many sources of TFP are so dependent on the heterogeneity of firms' total capital size. Specifically, our estimations show that large firms in terms of labor have significantly greater TFP levels than small firms in some fragmentations of a firms' capital size and in some manufacturing sectors. Similarly, we found significantly negative effects of labor quality, mixture effects of firms' ages, positively quick adjustments in productivity over time, mixture effects of firms' capital intensity, and positive effects of labor productivity in some low-tech manufacturing and medium high-tech manufacturing sectors, as well as the negative effect in the high-tech manufacturing sector, namely pharmaceuticals and medicinal chemicals (code 21).

Our results lead to some direct policy implications. Specifically, they point out that to explore firm productivity from the resource-based view, we need to master the heterogeneous firms' behavior. In other words, it is suggested that the government should build and improve relevant policies that are tailored within the Vietnamese firm characteristics so as to help them strengthen their operations and enhance productivity. Secondly, appropriate industrial policies to enhance TFP in each industry can be established so as to effectively maintain the sustainable industrialization of the country.

Despite our important findings toward firm productivity, the study still faces some limitations. That is, our analysis focused on the main internal determinants of TFP due to the insufficient sources of data, while external factors such as economic shocks and macroeconomic conditions can play important roles. Including external factors can induce more fruitful policy implications. Second, several internal factors, such as managerial and governance aspects, were not considered due to data limitations. Third, the limitation of the paper also comes from the interpretation of wage in terms of labor quality, since wages have many facets by themselves. Those issues will guide further research in the future.

Supplementary Materials: The following are available online at http://www.mdpi.com/2227-7099/8/3/57/s1: Table S1: Summary statistics for determinants of TFP in Vietnamese manufacturing firms. Table S2: Labor-heterogeneity determinants of TFP by industries, 2010–2015. Table S3: Capital-heterogeneity determinants of TFP by industries, 2010–2015.

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