J Prod Anal (2012) 38:285–302
DOI 10.1007/s11123-012-0273-3

Creative destruction over the business cycle: a stochastic frontier analysis

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Published online: 19 February 2012

Abstract This paper examines the within-industry distributions of jobs created and destructed across plants in terms of technical efficiency, technical efficiency change, scale effect, and technical change. It further investigates how these distributions vary with economic activity. By applying the stochastic frontier analysis to plant-level longitudinal data on Taiwan's 23 two-digit manufacturing industries spanning the period 1992–2003, we find that jobs created (destructed) are disproportionately clustered at plants with lower technical efficiency but higher rate of technical change. A fall in economic activities is associated with a statistically significant decrease (increase) in the fraction of newly created (destructed) jobs accounted for by plants with a higher rate of technical change, indicating that creative destruction is more pronounced during economic contractions.

Keywords Creative destruction · Job creation · Job destruction · Technical efficiency · Total factor productivity

JEL Classification D24 · E24 · E32

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1 Introduction

Previous literature on job reallocation has documented large simultaneous job creation and destruction. A natural question thus arises: are the observed creation and destruction primarily driven by the relative performance of firms or idiosyncratic shocks? Schumpeter (1939) argues that the process of creative destruction—the continuous replacement of obsolete production units with ones that embody the latest technology—is a major driving force of economic growth. Schumpeter further notes that recessions may ameliorate resource misallocation, because the least productive and least innovative units are the most likely to be scrapped in a recession.

Most previous empirical examinations of the efficiency of the reallocation process unfortunately measure micro-level productivity and technological change in a deterministic framework, confounding true productivity with idiosyncratic shocks outside the control of producers and rendering questionable the existing evidence on the roles of micro heterogeneity in the reallocation process. Moreover, there is not much work that studies the efficiency of creation and destruction separately.

This paper is one of the first to test for the presence of creative destruction in terms of plant performance measures purged of the effects of random shocks. We also establish and quantify the relationship between the efficiency of job reallocation and aggregate economic activity. By applying the stochastic frontier analysis (SFA) to a large panel of Taiwanese manufacturing plants, we measure each plant's technical efficiency (TE) and further decompose plant-level total factor productivity change $\left(\dot{TFP}\right)$ into technical efficiency change (TEΔ), technological change (TΔ), and scale effect (SC). The major advantage of the SFA approach is that the output effect of producer-specific idiosyncratic shocks can at least in principle be separated from the effect of changes in TE.

After obtaining efficiency and productivity measures purged of producer-specific random shocks, we proceed to test for two key hypotheses regarding the effectiveness of the resource reallocation process: the creative destruction hypothesis and the cleansing effect of recessions. More precisely, this paper addresses two questions. First, are jobs created (destructed) disproportionately located at plants with higher (lower) TE, TEΔ, and TΔ? Second, how does the distribution of jobs created (destructed) in terms of TE, TEΔ, and TΔ vary with the economic condition at the industry and aggregate levels?

The existing empirical studies on the effectiveness of reallocation have been inconclusive. Using data from the Great Depression, Bresnahan and Raff (1991) and Bertin et al. (1996) find no correlation between a plant's productivity and its exit probability. Olley and Pakes (1996) find that productivity growth in the US telecommunications equipment industry stems mainly from a reallocation of capital from less to more productive firms. Foster et al. (2001) conclude that the contribution of employment reallocation to aggregate productivity is greater during recessionary periods. Cantner and Krüger (2008) measure firm-level productivity of large German firms using data envelopment analysis and present that the driving forces of aggregate productivity growth are net entry and market share reallocation among continuers.

The improvements of this current paper upon the creative destruction literature are two-fold. First, for the first time in the literature, we document the distribution of jobs created and destructed across TE, TEΔ, TΔ, and SC to clarify the individual roles of these SFA-based plant performance indicators in the within-industry reallocation process. Second, we provide quantitative evidence on the cyclicality of the efficiency of the job creation (destruction) process by exploiting time series variation in the correlation between job creation (destruction) share and plant performance.

The rest of the paper proceeds as follows. Section 2 provides an overview of the theoretical predictions regarding the efficiency of the creative destruction process and then introduces and formulates the hypothesis to be tested. Section 3.1 outlines the SFA methodology used to generate the TE score, TEΔ, SC, and TΔ for each plant-year observation. Section 3.2 presents the Olley–Pakes decomposition methodology to measure the importance of plant performance indicators in the allocations of jobs created and destructed across plants. Section 4 describes the data source and sample statistics. Section 5 briefly explains the estimation results of the production frontiers and summarizes the estimated TE score, TEΔ, SC, and TΔ. Section 6.1 compares the technical efficiency and productivity change of the average created job with those of the average job destructed. Section 6.2 presents regression results on the association between the extent to which jobs created (destructed) are concentrated at high-performance plants and economic conditions. Section 7 concludes the paper.

2 The creative destruction hypothesis and the cleansing effect of recessions

2.1 The creative destruction hypothesis

In a market economy, profit-seeking firms are constantly being established while existing firms choose to exit, expand, or contract. Firms that embody the latest product and process innovations supplant firms that are less productive and innovative. Schumpeter (1942) coins the idea of creative destruction and describes this incessant shift of production resources away from less productive and innovative firms to more productive and innovative firms as the most important source of industry evolution and long-term economic growth. Aghion and Howitt (1992), Mortenson and Pissarides (1994), and Caballero and Hammour (1994, 1996) formally model the relationship between the process of creative destruction and aggregate productivity growth.

This paper defines creative destruction as a process of shifting factors of production away from underperforming plants towards outperforming plants. We gauge the effectiveness of the creative destruction process by examining whether the average TE (TEΔ and TΔ) of jobs created is significantly higher than the average TE (TEΔ and TΔ) of jobs destructed. In other words, a positive and statistically significant discrepancy between the average TE (TEΔ, TΔ) of jobs created and that of jobs destructed supports the creative destruction hypothesis.

2.2 The cleansing effect of recessions

The second hypothesis we intend to test is the cleansing effect of recessions, which is motivated by the theoretic debate on how business cycles impact the effectiveness of the reallocation process. Schumpeter (1934) and more recently Caballero and Hammour (1994, 1996) assert that recessions compel producers to use resources more efficiently, thereby releasing resources from production units with the most room for downsizing toward those with the least room for input reduction. In other words, recessions expedite the shift of resources from the least efficient production units to the more efficient ones, thus mitigating resource misallocation. From the viewpoints of these "liquidationists", recessions are times of cleansing, when the concentration of jobs destructed in low-productivity units increases.

In recent years a distinct line of literature has emerged to provide mechanisms whereby recessions exacerbate resource misallocation. Caballero and Hammour (2005) posit that in the presence of credit market frictions, productivity heterogeneity across producers may be less important in the selection mechanism. Barlevy (2003) argues that if projects that generate more surplus are also more vulnerable to credit constraints and that the credit market is imperfect, then recessions may destroy some of the more productive firms while preserving the less productive ones. Ouyang (2009) proposes that if plant-level productivity grows only gradually after entry, then recessions worsen resource allocation by forcing young but potentially innovative businesses to exit before they reach their full potential.

To assess which one of the two contrasting effects of recessions on the efficiency of reallocation dominates, we regress the covariance between the plant performance measure and the share of job creation (destruction) on a set of control variables and two indicators of the state of the economy. If the cleansing effects dominate the adverse effects caused by credit market frictions, then the extent to which destructed jobs are concentrated at high-performance plants should vary procyclically with the economy. On the other hand, if the cleansing effects are more than offset by the alternative effects, then the extent to which jobs destructed are concentrated at high-performance producers should be countercyclical.

3 Methodology

3.1 The stochastic production frontier model

We consider a logarithmic stochastic production frontier for the ith firm at time t as follows:

$$\ln Y_{it} = \ln f(X_{it}, t; \beta) + v_{it} - u_{it}, \quad i = 1, \ldots, n,\ t = 1, \ldots, T, \qquad (3-1)$$

where $\ln Y$ is the natural logarithm of output, $\ln f(\cdot)$ represents the natural logarithm of a production function, X is a $K \times 1$ vector of inputs, β denotes the technology parameter vector conformable to X, v signifies a two-sided i.i.d. normal random variable with mean zero and a constant variance σ_v^2, and technical inefficiency term u measures the distance of firm i's actual level of output at time t from the production frontier. We assume that the technical inefficiency term u is a half-normal random variable independent of v and has zero mean and a constant variance σ_u^2. This allows the pattern of TE evolution to be heterogeneous across plants.[1] Following Coelli et al. (2005, p. 300), we specify the production function $f(X_{it}, t; \beta)$ as a standard translog form with time trend (t). The interaction terms between t and the factors of production permit technical change to be non-neutral. The model in (3-1) is estimated using maximum likelihood.[2]

The key feature of the SFA approach is that the error term consists of a producer-specific random shock (v) and a technical inefficiency term (u). The inefficiency term u represents the management's capability to maximize output for a given level of inputs, while the random error v captures shocks uncontrollable by the producers. The output effect of managerial capability to organize inputs efficiently can at least in principle be isolated from the effects of producer-specific idiosyncratic shocks. Thus, the estimated efficiency score will not be contaminated by random shocks, thus reflecting true managerial ability.

The coefficient estimates of the frontier production function can be used to compute the following five indicators of plant efficiency and productivity: TE, TEΔ, TΔ, SC, and $T\dot{F}P$. The minimum mean squared error predictor of the TE score for firm i at time t is defined as

$$\mathrm{TE}_{it} = E(-u_{it} | e_{it}), \qquad (3-2)$$

where $e_{it} = v_{it} - u_{it}$. Simply put, a firm's TE score is measured as the ratio of the firm's observed output to its industry production frontier for a given input vector, after adjusting for producer-specific random shocks.

The Divisia index of total factor productivity change $\left(T\dot{F}P\right)$ is defined as the difference between the rate of change of output and the rate of change of an input quantity index. Kumbhakar and Lovell (2000) show that $T\dot{F}P$ can be expressed as:

$$T\dot{F}P = \mathrm{T}\Delta + \mathrm{SC} + \mathrm{TE}\Delta. \qquad (3-3)$$

Equation (3-3) shows that productivity change stems from three sources: technical change (TΔ), scale economies (SC), and TE change (TEΔ).[3] Specifically, the rate of

[1] In an earlier version of this paper, we used a production function that restricts the patterns of TE change to be the same for all firms—which is too restrictive for our intended purpose of analyzing the rate of technical efficiency change across plants. We thank the associate editor for pointing this out and suggesting to switch to this more flexible model.

[2] For the derivation of the likelihood function, see Aigner et al. (1977) and Chapter 3 of Kumbhakar and Lovell (2000). The maximum likelihood estimation of the half normal production function is carried out using the computer program Frontier 4.1, written by Professor Tim Coelli. Frontier 4.1 is available at http://www.uq.edu.au/economics/cepa/frontier.htm.

[3] According to Kumbhakar and Lovell (2000), TFP change consists of four as opposed to three terms. Specifically, $T\dot{F}P = \mathrm{T}\Delta + \mathrm{SC} + \sum_k \left[\left(\frac{\varepsilon_k}{\varepsilon}\right) - S_k\right] + \dot{X}_k + \mathrm{TE}\Delta$. That is, there should be a fourth term that captures the effect of allocative inefficiency in Eq. (3-3),

technical change, which measures the contribution of shifts in the production frontier, is given by:

$$\mathrm{T}\Delta = \frac{\partial \ln f(X,t;\beta)}{\partial t}. \quad (3-4)$$

From now on, the subscripts *i* and *t* are dropped for simplicity. The scale effect, which can be interpreted as the contribution of input use adjustment on productivity, is provided by

$$\mathrm{SC} = (\varepsilon - 1)\sum_k \frac{\varepsilon_k}{\varepsilon}\dot{X}_k, \quad (3-5)$$

where $\varepsilon_k = \varepsilon_k(X,t;\beta) = X_k f_k(X,t;\beta)/f(X,t;\beta)$, $k = 1, \ldots, K$, are the elasticities of output with respect to each of the inputs, and $f_k(X, t; \beta)$ is the partial derivative of the production function $f(.)$ with respect to input quantity X_k. The scale elasticity $\varepsilon = \varepsilon(X,t;\beta) = \sum_k \varepsilon_k(X,t;\beta)$ is a measure of returns to scale, with $\varepsilon > 1, = 1$, and < 1 corresponding to increasing, constant, and decreasing returns to scale, respectively. Finally, technical efficiency change is defined as:

$$\mathrm{TE}\Delta_{it} = -\frac{\partial u}{\partial t}. \quad (3-6)$$

Here, $\mathrm{TE}\Delta_{it}$ measures the rate at which the observed output moves toward the industry's maximum feasible output.

Multifactor productivity (MFP), which is calculated using the index number approach, is the most widely-used productivity index in the extant literature on the role of resource reallocation across heterogeneous production units in aggregate productivity growth.[4] To evaluate whether the SFA approach yields different implications on the contribution of resource reallocation to aggregate productivity growth from the index number approach, we compute the MFP index for each plant-year observation. Following Foster et al. (2001, 2006) and Foster et al. (2008), we define plant-level MFP as:

$$\mathrm{MFP}_{it} = \ln Y_{it} - \alpha_{Lt}\ln L_{it} - \alpha_{Kt}\ln K_{it}, \quad (3-7)$$

where the output elasticity of labor (α_{Lt}) is measured as the average share of the wage bill in output across plants in the industry. It should be noted that setting output elasticities equal to the factor income share implicitly assumes that factors are paid their marginal products, i.e., plants are allocatively efficient. As the price of capital service is not available, we measure the output elasticity of capital as one minus labor's share, i.e., $1-\alpha_{Lt}$.[5] Multifactor productivity growth between period *t*−*1* and *t* is calculated as:

$$\mathrm{MFP}\Delta = \ln\left(\frac{Y_{it}}{Y_{it-1}}\right) - \frac{1}{2}(\alpha_{Lt} + \alpha_{Lt-1})\ln\left(\frac{L_{it}}{L_{it-1}}\right) - \frac{1}{2}(\alpha_{Kt} + \alpha_{Kt-1})\ln\left(\frac{K_{it}}{K_{it-1}}\right). \quad (3-8)$$

It is noteworthy that MFP and MFPΔ differ from the efficiency and productivity measures obtained using the SFA approach in three important aspects.[6] First, and most importantly, MFP evaluates plant performance in a deterministic framework. Any variation in output not resulting from input growth is accredited to productivity. Hence, the resultant MFP measure of a plant's performance is likely to be confounded with random shocks outside the control of producers, such as weather, an oil shock, and a policy change. By contrast, the econometric approach of SFA explicitly accounts for noises and generates efficiency and productivity measures that are not contaminated by random shocks. Second, as is shown in Eq. (3-3), $T\dot{F}P$ can be decomposed into three components, thus providing further insights into the sources of productivity growth.[7] The MFPΔ in its simple form, however, does not distinguish among sources of productivity change. Third, measuring allocative inefficiency is in general possible in the SFA approach, but impossible in the index number approach. However, as mentioned in footnote 3, due to the unavailability of data on the price of capital service, in calculating $T\dot{F}P$ and MFPΔ, we have always maintained the assumption that plants are allocatively efficient.[8]

3.2 The Olley–Pakes decomposition methodology

Olley and Pakes (1996) introduce a cross-sectional decomposition approach to measure the extent to which activities are disproportionately located at more productive

Footnote 3 continued
but because data on the price of capital service are unavailable, we are unable to empirically calculate the allocative inefficiency term. We follow Kumbakhar and Lovell (2000, p. 284) to assume that factors are paid the value of their marginal product, i.e., plants attain allocative efficiency so that the allocative inefficiency term vanishes. We are indebted to the associated editor's suggestion to include the above discussion about the allocative inefficiency term in this paper.

4 For a survey of the literature on the role of output reallocation in aggregate productivity change, see Foster et al. (2001). For excellent reviews of the index number approach of measuring productivity, see Good et al. (1997) and Hulten (2009).

5 Note that calculating the output elasticity of capital as one minus labor's share in output implicitly assumes that the product market is perfectly competitive such that there is no markup. As a result, factor income shares add up to one and the production technology exhibits constant-returns-to-scale.

6 For an excellent review of the advantages and drawbacks on the index number approach and the SFA approach, see Chapter 12 of Coelli et al. (2005).

7 The main drawback of the SFA approach is its requirement of specifying a particular functional form for a production or a cost function, despite that the true functional forms are not known a priori.

8 We are indebted to the associate editor for pointing this out.

plants at a given point in time.[9] One novelty of this current paper is that for the first time in the literature, we apply Olley–Pakes decomposition to the industry-level weighted average productivity of jobs created (destructed).

Define industry j's weighted average TE of jobs created in time t (TEJC_{jt}) as the job creation share weighted average TE:

$$\mathrm{TEJC}_{jt} = \sum_{i \in j} s_{it}^{JC} \mathrm{TE}_{it}, \qquad (3-9)$$

where s_{it}^{JC} denotes plant i's share in total job creation for industry j at time t. The Olley–Pakes decomposition splits the industry-level weighted average TE of jobs created into two terms:

$$\begin{aligned}\mathrm{TEJC}_{jt} &= \overline{\mathrm{TE}}_{jt} + \sum_{i=1}^{N} \left(s_{it}^{JC} - \bar{s}_{t}^{JC}\right)\left(\mathrm{TE}_{it} - \overline{TE}_{jt}\right) \\ &= \overline{\mathrm{TE}}_{jt} + \mathrm{COVTEJC}_{jt}, \qquad (3-10)\end{aligned}$$

where $\bar{s}_{it}^{JC}$ is the unweighted average job creation share, $\overline{\mathrm{TE}}_{jt}$ is the unweighted average plant-level TE, and $\mathrm{COVTEJC}_{jt}$ is the cross-sectional covariance between a plant's TE and its share of total jobs created in the industry. A plant contributes positively to average productivity of jobs created if its TE exceeds (falls short of) the unweighted average TE in the industry and it occupies a higher (lower) job creation share than the unweighted average job creation share in the industry. A positive (negative) COVTEJC indicates that high-TE plants tend to occupy a greater (smaller) share in the industry's total jobs created.

The industry-level weighted average TE of jobs destructed (TEJD_{jt}) can be analogously decomposed as:

$$\mathrm{TEJD}_{jt} = \overline{\mathrm{TE}}_{jt} + \mathrm{COVTEJD}_{jt}, \qquad (3-11)$$

where $\mathrm{COVTEJC}_{jt}$ is the cross-sectional covariance between a plant's TE and its share in total jobs created in the industry. A negative (positive) COVTEJD indicates that low-TE plants tend to have a higher (lower) job destruction share. The more negative (positive) the term COVTEJD is, the more (less) aggregate productivity-enhancing is the job destruction process will be.

Regarding the test for the effectiveness of the creative destruction process, a positive and significant difference between mean COVTEJC and mean COVTEJD implies that the average TE of jobs created exceeds that of jobs destructed—an indication of creative destruction. It is illuminating to apply the Olley–Pakes decomposition to the industry-level weighted average TEΔ, TΔ, SC, and $T\dot{F}P$ of jobs created and destructed. The covariance terms in these decompositions will provide further insights into the importance of plant-level technical efficiency change and technical change in the restructuring process and the association between job creation (destruction) and scale efficiency.

4 Data description

The data are taken from the annual manufacturing plant census survey by the Ministry of Economic Affairs, Taiwan, the Republic of China, spanning from 1992 to 2003. The survey was not conducted in 1996 and 2001, reducing the data to 10 years. There are 23 two-digit manufacturing industries in our data.[10]

We measure plant output as value-added, which is constructed by subtracting from sales revenue the expenditures on materials, intermediate inputs, and electricity. Two inputs are identified from the data: labor (number of employees) and capital stock (the book value of equipment and structures) net of depreciation. The variables capital and value-added are deflated by the wholesale price index with base year 2001.[11] After deleting observations with missing values, the final sample has 753,775 observations (120,808 plants). Table 1 reports the descriptive statistics.[12]

Table 2 presents the annual averages of job creation and destruction rates, employment growth, and the job reallocation rate by industry. The mean job creation rate ranges from 0.113 to 0.255 and the mean job destruction rate lies between 0.1 and 0.237. The large rates of expansion and contraction reveal that Taiwanese plants adjust their workforce swiftly in response to market conditions. This possibly reflects the less generous welfare state and job security provisions in Taiwan, rendering the labor adjustment costs relatively low. Furthermore, the high rates of job reallocation may be a result of the dominance of small firms, which are less able to differentiate and diversify their products, are vulnerable to shocks due to their high volatility of revenues, and are more prone to credit constraints. The foregoing distinguishes Taiwan's manufacturing industries from those of the rest of the world and makes them a unique sample worth examining.

5 Technical efficiency and productivity estimates

Table 3 summarizes the plant-level technical efficiency and productivity indicators calculated using the production

[9] The Olley–Pakes decomposition has been used in many empirical studies examining the importance of output and employment reallocation in aggregate productivity growth. See, for example, Foster et al. (2001), (2008), Eslava et al. (2004), and (2010).

[10] The two-digit industry classification codes have been changed twice during the sample period. The four-digit codes are used to retrieve a consistent two-digit industry classification.

[11] The average exchange rate over the period 1993–2003 was NT$30.47/US$1.

[12] For brevity the same statistics for individual industries are not shown but are available upon request.

Table 1 Summary statistics

Variable	Mean	SD	Min	Max	No. of obs.
Number of employees	27	108	1	12,850	753,775
Value-added	34,617.080	447,384.000	0.947	134,000,000	753,775
Value-added per employee	720.630	2,157.446	0.032	1,219,656	753,775
Capital	66,132.590	1,277,400.000	0.947	282,000,000	753,775
Capital per employee	1,569.243	9,755.578	0.015	4,577,349	753,775
Industry real output growth	4.68%	11.46%	−0.15%	56.93%	207
Per capita real GDP growth	5.26%	2.68%	−2.17%	7.85%	10

Value-added and capital variables are measured in thousands of 2001 New Taiwan Dollars

Table 2 Job creation rate, job destruction rate, employment growth, and job reallocation rate by industry

SIC	Description	Job creation rate	Job destruction rate	Employment growth	Job reallocation rate
8	Food and beverage	0.158	0.167	−0.010	0.326
10	Textile	0.130	0.151	−0.051	0.281
11	Garment and apparel	0.199	0.236	−0.021	0.435
12	Leather, fur and leather and fur products	0.132	0.211	−0.028	0.344
13	Wood and bamboo products	0.156	0.237	−0.114	0.393
14	Furniture and furnishings	0.163	0.212	−0.076	0.376
15	Paper pulp, paper and paper products	0.126	0.145	−0.034	0.271
16	Printing	0.202	0.193	0.014	0.396
17	Chemical materials	0.113	0.100	0.016	0.212
18	Chemical products	0.160	0.153	0.006	0.312
19	Petroleum and coal products	0.068	0.140	−0.021	0.207
20	Rubber products	0.149	0.151	−0.017	0.300
21	Plastic products	0.185	0.198	−0.034	0.383
22	Non-metallic mineral products	0.157	0.191	−0.045	0.347
23	Basic metals	0.144	0.132	−0.001	0.276
24	Fabricated metal products	0.213	0.188	0.005	0.401
25	Machinery and equipment	0.219	0.194	0.052	0.413
26	Computer, telecommunications, audio and video electronics products	0.255	0.204	0.049	0.459
27	Electronics parts and components	0.225	0.142	0.106	0.367
28	Electrical equipment	0.183	0.187	−0.027	0.370
29	Transportation equipment	0.160	0.172	0.000	0.332
30	Precision machinery	0.199	0.189	0.002	0.388
31	Miscellaneous industrial products	0.192	0.234	−0.063	0.426
Mean		0.169	0.179	−0.013	0.348

Following Davis et al. (1996), the job creation (destruction) rate in year t is defined as the sum of jobs created (destructed) at all plants divided by the average of industry employment in years $t-1$ and t

frontier parameter estimates. The mean TE scores vary substantially across industries, ranging from 0.515 to 0.718. These figures show that even in the most efficient industry, the output of the average plant is 28.2% below that of the best-practice plant which uses the same input mix. The mean values of the TEΔ lie between −0.016 and 0.005. Mean TEΔ is negative in 21 out of the 23 cases, indicating that the output gap with the industry best practice widened at the typical plant.

The scale effect averaged negative in 14 industries, ranging from −0.021 to 0.005, indicating that changes in plant size improved productivity in only 9 out of the 23 industries. In the other 14 industries, input use adjustments are on average counterproductive.

Technical change is the dominant component among the three components of $\dot{TFP}$ in 22 of the 23 industries. The mean technical change ranges from −0.003 to 0.053. Here, TΔ is on average positive and large in magnitude.

Table 3 Sample statistics of efficiency and productivity measures by industry

SIC	Description (sample size)	TE	TEΔ	TΔ	SC	$T\dot{F}P$	MFP	MFPΔ	$\rho(T\dot{F}P, \mathrm{MFP}\Delta)$
8	Food and beverage (40228)	0.515	−0.009	0.035	0.005	0.031	0.245	−0.003	0.651
		(0.154)	(0.146)	(0.021)	(0.144)	(0.171)	(1.079)	(0.996)	
10	Textile (31413)	0.665	−0.006	0.035	−0.005	0.023	0.574	−0.020	0.728
		(0.098)	(0.095)	(0.011)	(0.067)	(0.101)	(0.812)	(0.788)	
11	Garment and apparel (14077)	0.692	−0.002	0.036	−0.011	0.022	0.759	0.001	0.614
		(0.080)	(0.077)	(0.022)	(0.086)	(0.103)	(0.895)	(0.821)	
12	Leather, fur and leather and fur products (5207)	0.638	−0.005	0.014	−0.012	−0.003	0.766	−0.050	0.715
		(0.111)	(0.106)	(0.039)	(0.094)	(0.129)	(0.874)	(0.780)	
13	Wood and bamboo products (14659)	0.569	−0.016	0.046	−0.004	0.026	0.491	−0.036	0.778
		(0.139)	(0.133)	(0.024)	(0.076)	(0.139)	(0.946)	(0.929)	
14	Furniture and furnishings (14083)	0.612	−0.010	0.045	−0.006	0.029	1.079	0.009	0.797
		(0.123)	(0.122)	(0.007)	(0.080)	(0.126)	(0.757)	(0.776)	
15	Paper pulp, paper and paper products (12735)	0.606	−0.016	0.053	0.000	0.037	0.664	−0.002	0.835
		(0.135)	(0.128)	(0.019)	(0.051)	(0.128)	(0.800)	(0.821)	
16	Printing (18512)	0.687	−0.003	0.028	−0.001	0.024	0.617	−0.009	0.721
		(0.100)	(0.098)	(0.013)	(0.060)	(0.099)	(0.729)	(0.690)	
17	Chemical materials (7698)	0.536	−0.012	0.045	−0.008	0.025	0.315	−0.002	0.717
		(0.158)	(0.144)	(0.026)	(0.118)	(0.160)	(1.012)	(0.955)	
18	Chemical products (16399)	0.607	−0.002	0.030	−0.007	0.021	0.008	−0.006	0.438
		(0.115)	(0.100)	(0.014)	(0.138)	(0.139)	(1.167)	(1.012)	
19	Petroleum and coal products (1135)	0.653	0.005	−0.003	−0.021	−0.019	0.706	−0.010	0.525
		(0.094)	(0.089)	(0.044)	(0.132)	(0.149)	(0.928)	(0.850)	
20	Rubber products (8977)	0.668	−0.006	0.027	0.000	0.021	0.742	−0.010	0.826
		(0.109)	(0.108)	(0.007)	(0.046)	(0.107)	(0.713)	(0.699)	
21	Plastic products (62712)	0.623	−0.011	0.037	0.001	0.028	0.739	−0.005	0.849
		(0.126)	(0.122)	(0.008)	(0.051)	(0.121)	(0.748)	(0.768)	
22	Non-metallic mineral products (22047)	0.618	−0.002	0.025	−0.015	0.007	0.744	−0.025	0.630
		(0.115)	(0.108)	(0.017)	(0.115)	(0.135)	(0.866)	(0.819)	
23	Basic metals (19581)	0.655	−0.003	0.033	−0.011	0.019	0.606	0.005	0.450
		(0.084)	(0.080)	(0.014)	(0.135)	(0.140)	(1.000)	(0.948)	
24	Fabricated metal products (96231)	0.677	−0.001	0.023	0.002	0.024	0.762	0.007	0.750
		(0.100)	(0.098)	(0.018)	(0.053)	(0.100)	(0.741)	(0.727)	
25	Machinery and equipment (95299)	0.661	−0.006	0.039	0.002	0.034	0.723	−0.002	0.757
		(0.106)	(0.104)	(0.014)	(0.062)	(0.106)	(0.806)	(0.768)	

Table 3 continued

SIC	Description (sample size)	TE	TEΔ	TΔ	SC	$\dot{TFP}$	MFP	MFPΔ	$\rho(\dot{TFP}, \text{MFP}\Delta)$
26	Computer, telecommunications, audio and video electronics products (15897)	0.706	0.000	0.046	0.000	0.045	0.968	0.018	0.439
		(0.058)	(0.059)	(0.025)	(0.108)	(0.117)	(0.986)	(0.018)	
27	Electronics parts and components (19133)	0.718	0.002	0.026	0.002	0.030	0.902	0.016	0.659
		(0.065)	(0.063)	(0.018)	(0.056)	(0.078)	(0.821)	(0.778)	
28	Electrical equipment (29760)	0.670	−0.003	0.036	−0.005	0.028	1.331	0.030	0.678
		(0.093)	(0.092)	(0.018)	(0.083)	(0.109)	(0.726)	(0.697)	
29	Transportation equipment (29979)	0.665	−0.006	0.044	0.002	0.039	0.627	−0.001	0.690
		(0.100)	(0.100)	(0.010)	(0.080)	(0.109)	(0.836)	(0.790)	
30	Precision machinery (10286)	0.677	−0.004	0.043	−0.007	0.033	0.760	−0.009	0.683
		(0.093)	(0.092)	(0.015)	(0.082)	(0.111)	(0.817)	(0.788)	
31	Miscellaneous industrial products (28062)	0.614	−0.010	0.042	−0.009	0.023	1.042	−0.005	0.757
		(0.120)	(0.118)	(0.012)	(0.089)	(0.129)	(0.772)	(0.776)	

This indicates that in order to survive fierce competition in the global market, Taiwanese plants had to constantly enhance their production technology.

Plant-level $\dot{TFP}$ averages positive in 21 of 23 industries, ranging from −0.019 to 0.045. This is because TΔ is sufficiently positive to entirely offset the negative effect of TEΔ and SC on productivity.

For comparison reason, we also report the summary statistics for MFP and MFPΔ. One striking finding that emerges is that MFP and MFPΔ are considerably more variable than TE and the three components of $\dot{TFP}$. The standard deviations of MFP and MFPΔ are much larger than that of TE and the three components of $\dot{TFP}$. Moreover, MFP and MFPΔ are more volatile, because MFP, which is generated in a deterministic setting, captures both productivity and idiosyncratic shocks. Nevertheless, the last column in Table 3, which reports the correlation coefficients between $\dot{TFP}$ and MFPΔ, indicates that MFPΔ and $\dot{TFP}$ are positively and significantly correlated in all industries.

6 Measuring the effectiveness of the creative destruction process and testing for the cleansing effects of recessions

6.1 The effectiveness of the creative destruction process

This section examines the distribution of jobs created (destructed) across technical efficiency and productivity indicators. We first consider the distribution of jobs created (destructed) across plants in terms of TE. Recall that a lower TE means that there are more idle resources and unproductive activities in the plant. Namely, a low-TE plant can substantially increase its output, holding constant the current input mix. Applying the Olley–Pakes decomposition to the weighted average TE of jobs created (destructed) enables us to assess whether jobs are destructed (created) mainly by plants with more (less) room for input reduction.

Table 4 summarizes the Olley–Pakes decomposition results for the weighted average TE of jobs created (destructed) as well as the p values of the test for the null hypothesis that the mean of the weighted average TE of jobs created and that of jobs destructed are equal.[13] The purpose of this test is to evaluate whether the average created job is significantly more technically efficient than the average destructed job.

[13] The numbers in columns one to three in Tables 4,5,6,7,8,9 and 10 are simple averages over time. Detailed results are available upon request.

Table 4 Decomposition of the industry-level weighted average technical efficiency of jobs created and destructed

SIC	Description	(1) $\overline{\text{TE}}$	(2) $\text{Cov}\left(\text{TE}_{it}, s_{it}^{JC}\right)$	(3) $\text{Cov}\left(\text{TE}_{it}, s_{it}^{JD}\right)$	(4) $\frac{(2)}{(1)+(2)}$	(5) $\frac{(3)}{(1)+(3)}$	(6) p value of mean comparison t test
8	Food and beverage	0.514	−0.025	0.017	−0.052	0.031	0.000
10	Textile	0.666	−0.008	0.006	−0.012	0.009	0.002
11	Garment and apparel	0.691	−0.010	0.015	−0.014	0.020	0.000
12	Leather, fur and leather and fur products	0.639	−0.009	0.007	−0.015	0.011	0.085
13	Wood and bamboo products	0.570	−0.028	0.026	−0.064	0.043	0.005
14	Furniture and furnishings	0.612	−0.017	0.022	−0.029	0.035	0.000
15	Paper pulp, paper, and paper products	0.605	−0.027	0.005	−0.047	0.007	0.002
16	Printing	0.686	−0.020	0.012	−0.030	0.016	0.000
17	Chemical materials	0.534	−0.006	−0.004	−0.017	−0.007	0.392
18	Chemical products	0.607	−0.007	0.025	−0.012	0.039	0.000
19	Petroleum and coal products	0.654	−0.020	0.017	−0.031	0.025	0.000
20	Rubber products	0.668	−0.010	0.012	−0.017	0.018	0.001
21	Plastic products	0.622	−0.022	0.007	−0.038	0.010	0.001
22	Non-metallic mineral products	0.618	−0.016	0.014	−0.027	0.022	0.003
23	Basic metals	0.655	−0.009	0.008	−0.014	0.011	0.000
24	Fabricated metal products	0.676	−0.015	0.015	−0.023	0.022	0.000
25	Machinery and equipment	0.660	−0.024	0.018	−0.038	0.027	0.000
26	Computer, telecommunications, audio and video electronics products	0.706	−0.005	0.007	−0.007	0.009	0.054
27	Electronics parts and components	0.718	−0.005	0.004	−0.007	0.006	0.053
28	Electrical equipment	0.670	−0.012	0.013	−0.019	0.019	0.003
29	Transportation equipment	0.665	−0.012	0.011	−0.018	0.016	0.008
30	Precision machinery	0.677	−0.010	0.010	−0.016	0.014	0.006
31	Miscellaneous industrial products	0.615	−0.041	0.007	−0.093	0.009	0.045
Mean		0.640	−0.016	0.012	−0.028	0.018	

Column (1) shows the contribution of the simple mean of TE. Columns (2) and (3) show the contribution of the cross-sectional correlation between TE and job creation share and job destruction share, respectively. All of the figures in columns one through three are simple means for those two-digit industry level statistics across time. Column (4) shows the fractions of the weighted average TE of jobs created represented by the covariance term. Column (5) shows the fractions of the weighted average TE of jobs destructed represented by the covariance term. The p values in column (6) are results from t tests on the null hypothesis that the mean of the weighted average TE of jobs created and that of jobs destructed are equal against the alternative hypothesis that the mean of the weighted average TE of jobs created is less than the mean of the weighted average TE of jobs destructed

Three striking findings emerge. First, $\text{Cov}\left(\text{TE}_{it}, s_{it}^{JC}\right)$ is negative in all industries and $\text{Cov}\left(\text{TE}_{it}, s_{it}^{JD}\right)$ is positive in 22 of the 23 industries, suggesting that job creation is disproportionately located at low-TE plants, whereas job destruction is disproportionately located at high-TE plants. Depending on the industry, the weighted average TE of jobs created (destructed) would be 0.005–0.041 higher (0.026 lower–0.004 higher) if jobs created (destructed) were randomly allocated across plants. The results thus indicate that many inefficient plants increase their hiring in spite of having low managerial skills and idle resources. In contrast, high-TE plants cut jobs even though their managerial skills are already superior and room for improving technical efficiency is limited.

Second, the weighted average TE of jobs created (destructed) is mainly accounted for by the unweighted average TE, indicating that the importance of TE in gaining job creation (destruction) share is marginal. Third, the null hypothesis that—the TE of the average job created is equal to that of the average job destroyed—is rejected at the 5% level in 21 of the 23 cases. The evidence points to the fact that that less efficient jobs displace more efficient jobs in 21 industries. In short, when plant performance is measured by TE, our data do not support the creative destruction hypothesis.

We next turn to examine the TEΔ distribution of jobs created and destructed. Table 5 reports the Olley–Pakes decomposition results for the weighted average TEΔ of jobs created (destructed). Here, $\text{Cov}\left(\text{TE}\Delta_{it}, s_{it}^{JC}\right)$ is negative in all industries whereas $\text{Cov}\left(\text{TE}\Delta_{it}, s_{it}^{JD}\right)$ turns out positive in all industries. The null hypothesis that the weighted average TEΔ of jobs created and that of jobs

Table 5 Decomposition of the industry-level weighted average rate of technical efficiency change of jobs created and destructed

SIC	Description	(1) $\overline{\mathrm{TE}\Delta}$	(2) $\mathrm{Cov}\left(\mathrm{TE}\Delta_{it}, s_{it}^{JC}\right)$	(3) $\mathrm{Cov}\left(\mathrm{TE}\Delta_{it}, s_{it}^{JD}\right)$	(4) $\frac{(2)}{(1)+(2)}$	(5) $\frac{(3)}{(1)+(3)}$	(6) p value of mean comparison t test
8	Food and beverage	−0.010	−0.049	0.040	−3.240	1.487	0.000
10	Textile	−0.005	−0.027	0.017	0.682	7.600	0.000
11	Garment and apparel	−0.003	−0.031	0.016	1.050	−0.588	0.000
12	Leather, fur and leather and fur products	−0.005	−0.028	0.014	0.718	2.418	0.003
13	Wood and bamboo products	−0.015	−0.066	0.040	0.589	8.144	0.000
14	Furniture and furnishings	−0.010	−0.044	0.030	0.607	−0.392	0.000
15	Paper pulp, paper and paper products	−0.016	−0.048	0.033	0.561	5.812	0.000
16	Printing	−0.004	−0.045	0.022	1.532	1.295	0.000
17	Chemical materials	−0.014	−0.031	0.027	0.241	−20.074	0.000
18	Chemical products	−0.002	−0.039	0.030	1.000	1.275	0.000
19	Petroleum and coal products	0.005	−0.028	0.015	3.343	0.307	0.010
20	Rubber products	−0.006	−0.034	0.024	0.500	1.222	0.000
21	Plastic products	−0.011	−0.042	0.025	0.616	1.835	0.000
22	Non-metallic mineral products	−0.002	−0.039	0.030	0.986	2.484	0.000
23	Basic metals	−0.003	−0.012	0.014	−37.088	2.946	0.000
24	Fabricated metal products	−0.002	−0.035	0.028	1.127	1.248	0.000
25	Machinery and equipment	−0.007	−0.043	0.032	0.461	2.264	0.000
26	Computer, telecommunications, audio and video electronic products	−0.001	−0.016	0.010	1.028	0.662	0.000
27	Electronics parts and components	0.002	−0.011	0.013	1.065	0.877	0.002
28	Electrical equipment	−0.003	−0.028	0.031	−0.028	1.002	0.002
29	Transportation equipment	−0.007	−0.034	0.019	0.404	1.001	0.000
30	Precision machinery	−0.004	−0.023	0.015	0.730	1.503	0.001
31	Miscellaneous industrial products	−0.009	−0.067	0.036	0.569	0.870	0.002
Mean		−0.006	−0.036	0.024	−0.980	1.096	

Column (1) shows the contribution of the simple mean of TEΔ. Columns (2) and (3) show the contribution of the cross-sectional correlation between TEΔ and job creation share and job destruction share, respectively. All of the figures in columns one through three are simple means for those two-digit industry level statistics across time. Column (4) shows the fractions of the weighted average TEΔ of jobs created represented by the covariance term. Column (5) shows the fractions of the weighted average TEΔ of jobs destructed represented by the covariance term. The p values in column (6) are results from t tests on the null hypothesis that the mean of the weighted average TEΔ of jobs created and that of jobs destructed are equal against the alternative hypothesis that the mean of weighted average TEΔ of jobs created is less than the mean of the weighted average TEΔ of jobs destructed

destructed are equal is rejected at the 5% level in all 23 industries. The covariance terms imply that if jobs created (destructed) were randomly allocated, then the industry-level weighted average TEΔ of jobs created (destructed) would be 0.011–0.067 higher (0.01–0.04 lower). Therefore, results obtained using technical efficiency change as a plant performance measure are counter to the creative destruction hypothesis.

The finding that job destruction (creation) is associated with a higher (lower) rate of technical efficiency change is not surprising. As Table 4 shows, jobs are primarily destructed by plants with better managerial skills, i.e., high-TE plants. Further employment reduction in plants that are already highly efficient boosts technical efficiency. Conversely, since new jobs are primarily created by plants that could produce more output with the same level of inputs, adding jobs in these less efficient plants exacerbates technical inefficiency.

We now turn our attention to the distribution of jobs created (destructed) across TΔ. Table 6 presents the Olley–Pakes decomposition results for the weighted average TΔ of jobs created (destructed). We find that $\mathrm{Cov}\left(\mathrm{T}\Delta_{it}, s_{it}^{JC}\right)$ is positive in 20 of the 23 industries, implying that in most industries jobs created are disproportionately concentrated at high-TΔ plants. Somewhat surprisingly, $\mathrm{Cov}\left(\mathrm{T}\Delta_{it}, s_{it}^{JD}\right)$ is positive in 13 of the 23 industries, which means that in more than half of the industries, destructed jobs are also disproportionately clustered at high-TΔ plants. Nevertheless, the null hypothesis that the TΔ of the average job created is equal to that of the average job destructed is rejected in 22 of the 23 cases at the 5% level, confirming that the TΔ of the

Table 6 Decomposition of the industry-level weighted average rate of technical change of jobs created and destructed

SIC	Description	(1) $\overline{\text{T}\Delta}$	(2) $\text{Cov}\left(\text{T}\Delta_{it}, s_{it}^{JC}\right)$	(3) $\text{Cov}\left(\text{T}\Delta_{it}, s_{it}^{JD}\right)$	(4) $\frac{(2)}{(1)+(2)}$	(5) $\frac{(3)}{(1)+(3)}$	(6) p value of mean comparison t test
8	Food and beverage	0.035	0.018	0.005	0.352	0.127	0.000
10	Textile	0.034	0.004	0.001	0.118	0.013	0.000
11	Garment and apparel	0.037	0.006	0.002	0.244	0.108	0.000
12	Leather, fur, and leather and fur products	0.019	0.016	0.007	−0.264	0.253	0.001
13	Wood and bamboo products	0.050	0.022	0.007	0.330	0.131	0.000
14	Furniture and furnishings	0.045	0.008	0.003	0.143	0.071	0.000
15	Paper pulp, paper, and paper products	0.054	0.007	0.001	0.118	0.007	0.000
16	Printing	0.028	0.009	0.003	0.273	0.089	0.000
17	Chemical materials	0.046	0.002	−0.007	0.036	−0.179	0.003
18	Chemical products	0.030	−0.002	−0.003	−0.072	−0.163	0.009
19	Petroleum and coal products	0.004	0.002	−0.018	−0.037	1.823	0.000
20	Rubber products	0.027	0.000	−0.003	−0.015	−0.129	0.000
21	Plastic products	0.037	0.005	0.000	0.117	−0.008	0.000
22	Non-metallic mineral products	0.023	−0.001	−0.003	−0.021	0.243	0.005
23	Basic metals	0.033	−0.010	−0.010	−0.464	−0.455	0.390
24	Fabricated metal products	0.022	0.004	0.001	0.088	−0.091	0.000
25	Machinery and equipment	0.040	0.005	0.000	0.114	0.006	0.000
26	Computer, telecommunications, audio and video electronics products	0.045	0.001	−0.005	0.069	0.800	0.003
27	Electronics parts and components	0.026	0.002	−0.001	0.155	−0.001	0.011
28	Electrical equipment	0.034	0.002	−0.001	0.079	−0.095	0.000
29	Transportation equipment	0.044	0.001	−0.001	0.027	−0.034	0.000
30	Precision machinery	0.042	0.015	0.006	0.269	0.118	0.000
31	Miscellaneous industrial products	0.041	0.015	0.004	0.257	0.091	0.000
Mean		0.035	0.006	−0.001	0.083	0.119	

Column (1) shows the contribution of the simple mean of TΔ. Columns (2) and (3) show the contribution of the cross-sectional correlation between TΔ and job creation share and job destruction share, respectively. All of the figures in columns one through three are simple means for those two-digit industry level statistics across time. Column (4) shows the fractions of the weighted average TΔ of jobs created represented by the covariance term. Column (5) shows the fractions of the weighted average TΔ of jobs destructed represented by the covariance term. The p values in column (6) are results from t tests on the null hypothesis that the mean of the weighted average TΔ of jobs created and that of jobs destructed are equal against the alternative hypothesis that the mean of the weighted average TΔ of jobs created is greater than the mean of the weighted average TΔ of jobs destructed

average job created is higher than that of the average job destructed. Thus, the creative destruction hypothesis is supported by the data when plant performance is proxied by the rate of technical change.

Table 7 shows the association between creation (destruction) and changes in scale efficiency. Measure $\text{Cov}\left(\text{SC}_{it}, s_{it}^{JC}\right)$ is found to be positive, whereas $\text{Cov}\left(\text{SC}_{it}, s_{it}^{JD}\right)$ is found to be negative in all industries, suggesting that the larger the job creation (destruction) share is, the greater (smaller) the change in scale efficiency will be. The foregoing implies that if jobs created (destructed) were randomly allocated, then depending on the industry the weighted average SC of jobs created (destructed) would be 0.034–0.15 lower (0.044–0.132 higher). The finding that job creation (destruction) enhances (hampers) scale efficiency implies that both creation and destruction are disproportionately located at increasing-returns-to-scale plants.

Table 8 presents the decomposition results for the weighted average rate of $\left(T\dot{F}P\right)$ change for jobs created and destructed. $\text{Cov}\left(T\dot{F}P_{it}, s_{it}^{JC}\right)$ is positive in all industries whereas $\text{Cov}\left(T\dot{F}P_{it}, s_{it}^{JD}\right)$ is negative in all industries. The null hypothesis that the $T\dot{F}P$ of the average job created is equal to that of the average job destructed is rejected at the 5% level in all industries. At first glance, this finding seems to support the creative destruction hypothesis. Following Eq. (3-3), the covariance between $T\dot{F}P$ and job creation (destruction) share can be expressed as the sum of three individual covariance terms:

Table 7 Decomposition of the industry-level weighted average scale effect of jobs created and destructed

SIC	Description	(1) $\overline{\mathrm{SC}}$	(2) $\mathrm{Cov}\left(\mathrm{SC}_{it}, s_{it}^{JC}\right)$	(3) $\mathrm{Cov}\left(\mathrm{SC}_{it}, s_{it}^{JD}\right)$	(4) $\frac{(2)}{(1)+(2)}$	(5) $\frac{(3)}{(1)+(3)}$	(6) p value of mean comparison t test
8	Food and beverage	0.005	0.150	−0.132	0.978	1.041	0.000
10	Textile	−0.005	0.060	−0.046	1.104	0.893	0.000
11	Garment and apparel	−0.011	0.073	−0.055	1.193	0.820	0.000
12	Leather, fur, and leather and fur products	−0.011	0.102	−0.062	1.139	0.916	0.000
13	Wood and bamboo products	−0.006	0.117	−0.086	1.070	0.944	0.000
14	Furniture and furnishings	−0.007	0.075	−0.057	1.109	0.887	0.000
15	Paper pulp, paper, and paper products	0.000	0.066	−0.044	1.003	0.996	0.000
16	Printing	−0.001	0.074	−0.057	1.008	0.990	0.000
17	Chemical materials	−0.008	0.034	−0.058	1.595	0.858	0.000
18	Chemical products	−0.007	0.090	−0.119	1.108	0.925	0.000
19	Petroleum and coal products	−0.019	0.041	−0.052	1.542	0.727	0.001
20	Rubber products	0.000	0.059	−0.049	1.006	1.004	0.000
21	Plastic products	0.001	0.081	−0.054	0.988	1.020	0.000
22	Non-metallic mineral products	−0.016	0.065	−0.087	1.377	0.833	0.000
23	Basic metals	−0.011	0.041	−0.090	1.251	0.871	0.000
24	Fabricated metal products	0.002	0.066	−0.052	0.976	1.034	0.000
25	Machinery and equipment	0.002	0.090	−0.067	0.983	1.031	0.000
26	Computer, telecommunications, audio and video electronics products	−0.001	0.118	−0.085	1.013	0.998	0.000
27	Electronics parts and components	0.002	0.065	−0.045	0.981	1.063	0.000
28	Electrical equipment	−0.006	0.067	−0.072	1.115	0.899	0.000
29	Transportation equipment	0.001	0.114	−0.081	0.997	1.000	0.000
30	Precision machinery	−0.007	0.068	−0.063	1.124	0.877	0.000
31	Miscellaneous industrial products	−0.009	0.039	−0.078	1.100	0.895	0.045
Mean		−0.005	0.076	−0.069	1.120	0.936	

Column (1) shows the contribution of the simple mean of SC. Columns (2) and (3) show the contribution of the cross-sectional correlation between SC and job creation share and job destruction share, respectively. All of the figures in columns one through three are simple means for those two-digit industry level statistics across time. Column (4) shows the fractions of the weighted average SC of jobs created represented by the covariance term. Column (5) shows the fractions of the weighted average SC of jobs destructed represented by the covariance term. The p values in column (6) are results from t tests on the null hypothesis that the mean of the weighted average SC of jobs created and that of jobs destructed are equal against the alternative hypothesis that the mean of the weighted average SC of jobs created is greater than the mean of the weighted average SC of jobs destructed

$$\mathrm{Cov}\left(T\dot{F}P_{it}, s_{it}^{JX}\right) = \mathrm{Cov}\left(\mathrm{TE}\Delta_{it}, s_{it}^{JX}\right) + \mathrm{Cov}\left(\mathrm{T}\Delta_{it}, s_{it}^{JX}\right) + \mathrm{Cov}\left(\mathrm{SC}_{it}, s_{it}^{JX}\right),$$

where X denotes either JC or JD.

Based on Tables 5, 6, 7, the covariance between SC and job creation (destruction) share is the largest in absolute value and thus dominates the other two covariance terms. The negative (positive) effect of $\mathrm{Cov}\left(\mathrm{TE}\Delta_{it}, s_{it}^{JC}\right)$ $\left(\mathrm{Cov}\left(\mathrm{TE}\Delta_{it}, s_{it}^{JD}\right)\right)$ is entirely outweighed by the positive (negative) effect of $\mathrm{Cov}\left(\mathrm{SC}_{it}, s_{it}^{JC}\right)$ $\left(\mathrm{Cov}\left(\mathrm{SC}_{it}, s_{it}^{JD}\right)\right)$. It is clear that if the efficiency of job reallocation is analyzed solely in terms of plant-level $T\dot{F}P$, then facts that job creation (destruction) tends to improve (impede) scale efficiency and the average TEΔ of jobs created is lower than that of the average job destructed cannot be detected. The above decomposition exercises reveal that, to draw sensible conclusions about the efficiency of the restructuring process, it is essential to delve deeper into the distribution of jobs created and destructed along all of the four dimensions: TE, TEΔ, TΔ, and SC.

We have so far documented that market selection is better characterized as a selection on plants' technological innovation, as opposed to a selection on technical efficiency or the rate of technical efficiency change. The rate of technical change is more important than technical efficiency in gaining employment share. One possible reason for this is that due to rapidly rising domestic wages and intensified competition from emerging economies, small and technically efficient plants that cannot afford R&D expenditures (and consequently are less technologically innovative) choose to outsource or move to low-cost countries. Conversely, plants that continue to create jobs

Table 8 Decomposition of the industry-level weighted average rate of $\left(\dot{TFP}\right)$ change of jobs created and destructed

SIC	Description	(1) $\overline{\dot{TFP}}$	(2) $\mathrm{Cov}\left(\dot{TFP}_{it}, s_{it}^{JC}\right)$	(3) $\mathrm{Cov}\left(\dot{TFP}_{it}, s_{it}^{JD}\right)$	(4) $\frac{(2)}{(1)+(2)}$	(5) $\frac{(3)}{(1)+(3)}$	(6) p value of mean comparison t test
8	Food and beverage	0.031	0.119	−0.087	0.803	1.928	0.000
10	Textile	0.023	0.037	−0.029	0.718	0.581	0.000
11	Garment and apparel	0.022	0.048	−0.037	0.748	−1.543	0.000
12	Leather, fur, and leather and fur products	0.003	0.090	−0.042	1.174	1.712	0.000
13	Wood and bamboo products	0.030	0.073	−0.039	0.778	0.155	0.000
14	Furniture and furnishings	0.028	0.039	−0.024	0.748	2.526	0.000
15	Paper pulp, paper, and paper products	0.038	0.025	−0.010	0.010	−0.638	0.007
16	Printing	0.023	0.039	−0.032	0.620	2.456	0.002
17	Chemical materials	0.024	0.005	−0.038	0.082	0.703	0.013
18	Chemical products	0.021	0.050	−0.092	0.785	1.480	0.000
19	Petroleum and coal products	−0.009	0.016	−0.056	0.286	−1.154	0.001
20	Rubber products	0.021	0.025	−0.028	0.418	0.815	0.000
21	Plastic products	0.027	0.044	−0.029	0.507	−0.104	0.000
22	Non-metallic mineral products	0.005	0.026	−0.060	1.386	−0.170	0.001
23	Basic metals	0.020	0.019	−0.087	−0.142	1.662	0.000
24	Fabricated metal products	0.022	0.035	−0.024	0.679	−5.629	0.000
25	Machinery and equipment	0.035	0.052	−0.035	0.622	−0.243	0.000
26	Computer, telecommunications, audio and video electronics products	0.044	0.104	−0.080	0.717	0.204	0.000
27	Electronics parts and components	0.030	0.057	−0.032	0.669	0.639	0.000
28	Electrical equipment	0.026	0.040	−0.042	0.717	0.988	0.000
29	Transportation equipment	0.038	0.081	−0.063	0.684	1.531	0.000
30	Precision machinery	0.032	0.061	−0.042	0.636	4.858	0.000
31	Miscellaneous industrial products	0.022	−0.014	−0.038	0.842	1.904	0.385
Mean		0.024	0.046	−0.045	0.630	0.637	

Column (1) shows the contribution of the simple mean of $\dot{TFP}$. Columns (2) and (3) show the contribution of the cross-sectional correlation between $\dot{TFP}$ and job creation share and job destruction share, respectively. All of the figures in columns one through three are simple means for those two-digit industry level statistics across time. Column (4) shows the fractions of the weighted average $\dot{TFP}$ of jobs created represented by the covariance term. Column (5) shows the fractions of the weighted average $\dot{TFP}$ of jobs destructed represented by the covariance term. The p values in column (6) are results from t tests on the null hypothesis that the mean of the weighted average $\dot{TFP}$ of jobs created and that of jobs destructed are equal against the alternative hypothesis that the mean of the weighted average $\dot{TFP}$ of jobs created is greater than the mean of the weighted average $\left(\dot{TFP}\right)$ of jobs destructed

domestically are primarily those that seek to gain a competitive edge through R&D investment as opposed to outsourcing or undertaking outward foreign direct investment.

Since most previous empirical studies on the efficiency of reallocation mainly use MFP, we apply the Olley–Pakes decomposition to the industry-level weighted average MFP of jobs created (destructed). This allows us to assess whether the SFA and the index number approach yield different implications about the importance of efficiency and productivity heterogeneities in the distribution of jobs created (destructed).

Table 9 reports the Olley–Pakes decomposition results for the weighted average MFP of jobs created (destructed). Both job creation and destruction are disproportionately clustered at high-MFP plants. The null hypothesis that the mean of the weighted average MFP of jobs created and that of jobs destructed are equal is rejected against the alternative hypothesis that the mean of the weighted average MFP of jobs created is higher than that of jobs destructed in 11 of 23 industries. This is inconsistent with our decomposition results for the weighted average TE of jobs created (destructed), which indicates that the weighted average TE of jobs created is significantly lower than that of the weighted average TE of jobs destructed in most industries.

It is pivotal to note that the share of the industry-level weighted average MFP of jobs created (destructed) explained by the covariance term is much higher than the share of industry-level weighted average TE of jobs created (destructed) explained by the covariance term. Specifically, the average fraction of the weighted average MFP of jobs

Table 9 Decomposition of aggregate multifactor productivity of jobs created and destructed

SIC	Description	(1) $\overline{\text{MFP}}$	(2) $\text{Cov}\left(\text{MFP}_{it}, s_{it}^{JC}\right)$	(3) $\text{Cov}\left(\text{MFP}_{it}, s_{it}^{JD}\right)$	(4) $\frac{(2)}{(1)+(2)}$	(5) $\frac{(3)}{(1)+(3)}$	(6) p value of mean comparison t test
8	Food and beverage	0.249	0.586	0.520	0.702	0.676	0.150
10	Textile	0.579	0.156	0.033	0.212	0.054	0.007
11	Garment and apparel	0.762	0.327	0.242	0.300	0.241	0.074
12	Leather, fur, and leather and fur products	0.783	0.331	0.181	0.297	0.188	0.016
13	Wood and bamboo products	0.488	0.192	0.199	0.283	0.289	0.521
14	Furniture and furnishings	1.107	0.138	0.271	0.111	0.197	0.992
15	Paper pulp, paper, and paper products	0.669	0.081	0.050	0.108	0.069	0.230
16	Printing	0.611	0.148	0.109	0.195	0.151	0.227
17	Chemical materials	0.317	0.101	−0.082	0.242	−0.348	0.022
18	Chemical products	0.010	0.419	0.177	0.976	0.945	0.002
19	Petroleum and coal products	0.770	0.113	0.147	0.128	0.160	0.674
20	Rubber products	0.743	0.181	0.052	0.196	0.065	0.006
21	Plastic products	0.742	0.178	0.138	0.194	0.157	0.207
22	Non-metallic mineral products	0.739	0.182	0.145	0.197	0.164	0.311
23	Basic metals	0.631	0.116	0.009	0.156	0.015	0.034
24	Fabricated metal products	0.770	0.164	0.108	0.175	0.123	0.074
25	Machinery and equipment	0.721	0.209	0.153	0.225	0.175	0.079
26	Computer, telecommunications, audio and video electronics products	0.981	0.420	0.248	0.300	0.201	0.064
27	Electronics parts and components	0.925	0.135	0.074	0.127	0.075	0.234
28	Electrical equipment	1.361	0.188	0.312	0.122	0.187	0.988
29	Transportation equipment	0.629	0.295	0.176	0.319	0.218	0.060
30	Precision machinery	0.767	0.278	0.133	0.266	0.148	0.052
31	Miscellaneous industrial products	1.058	−0.040	0.196	−0.040	0.156	0.822
Mean		0.714	0.213	0.156	0.252	0.187	

Column (1) shows the contribution of the simple mean of MFP. Columns (2) and (3) show the contribution of cross-sectional correlation between MFP and job creation share and job destruction share, respectively. All of the figures in columns one through three are simple means for those two-digit industry level statistics across time. Column (4) shows the fractions of the weighted average MFP of jobs created represented by the covariance term. Column (5) shows the fractions of the weighted average MFP of jobs destructed represented by the covariance term. The p values in column (6) are results from t tests on the null hypothesis that the mean of the weighted average MFP of jobs created and that of jobs destructed are equal against the alternative hypothesis that the mean of the weighted average MFP of jobs created is greater than the mean of the weighted average MFP of jobs destructed

created (destructed) accounted for by the covariance term is 25.2% (18.7%). This leads to an impression that plant-level productivity plays an important role in the allocation of jobs. On the other hand, based on the results in Table 4, the covariance term accounts for only −2.8% (1.8%) of the weighted average TE of jobs created (destructed). Such discrepancy presumably has to do with the greater dispersion of MFP, which is likely a manifestation of idiosyncratic shocks. The stark difference between the SFA results and MFP results is important, as it signifies that using plant performance measures not purged of idiosyncratic shocks is apt to overstate the role of productivity heterogeneity in resource reallocation while entirely overlooking the influence of random shocks on the efficiency of resource allocation.

Table 10 presents the decomposition results of the average MFPΔ of jobs created (destructed). Job creation (destruction) share is positively (negatively) correlated with MFPΔ in 15 (13) of the 23 industries. The null hypothesis that the MFPΔ of the average job created is equal to that of the average job destructed cannot be rejected in 17 out of the 23 cases. This contrasts sharply with the result obtained using TΔ as the plant performance indicator. Moreover, the fraction of the weighted average MFPΔ of jobs created (destructed) accounted for by the covariance term is 159.7% (67%), whereas the fraction of the weighted average TΔ accounted for by the covariance term is only 8.3% (11.9%). Similar to the results obtained using MFP as the plant performance measure, this implies that using performance measures not purged of random

Table 10 Decomposition of the industry-level weighted average multifactor productivity growth of jobs created and destructed

SIC	Description	(1) $\overline{\text{MFP}\Delta}$	(2) $\text{Cov}(\text{MFP}\Delta_{it}, s_{it}^{JC})$	(3) $\text{Cov}(\text{MFP}\Delta_{it}, s_{it}^{JD})$	(4) $\frac{(2)}{(1)+(2)}$	(5) $\frac{(3)}{(1)+(3)}$	(6) p value of mean comparison t test
8	Food and beverage	−0.007	0.041	0.006	1.194	−5.786	0.290
10	Textile	−0.016	0.037	−0.009	1.738	0.364	0.117
11	Garment and apparel	−0.011	0.040	−0.020	1.406	0.638	0.173
12	Leather, fur, and leather and fur products	−0.028	0.086	−0.063	1.492	0.690	0.019
13	Wood and bamboo products	−0.031	−0.070	0.067	0.693	1.859	0.853
14	Furniture and furnishings	0.005	−0.157	0.121	1.033	0.960	1.000
15	Paper pulp, paper, and paper products	−0.002	−0.012	0.046	0.884	1.036	0.819
16	Printing	−0.012	−0.023	−0.027	0.666	0.698	0.470
17	Chemical materials	0.001	0.028	−0.026	0.978	1.025	0.169
18	Chemical products	−0.007	0.106	−0.152	1.075	0.954	0.001
19	Petroleum and coal products	0.012	0.104	0.006	0.898	0.336	0.269
20	Rubber products	−0.011	0.012	−0.060	15.059	0.848	0.082
21	Plastic products	−0.006	−0.002	0.004	0.217	−1.618	0.542
22	Non-metallic mineral products	−0.030	−0.027	0.037	0.480	4.899	0.773
23	Basic metals	0.004	0.123	−0.068	0.966	1.068	0.006
24	Fabricated metal products	0.000	0.022	−0.005	0.983	1.073	0.309
25	Machinery and equipment	0.002	0.029	−0.022	0.941	1.089	0.118
26	Computer, telecommunications, audio and video electronics products	0.015	0.052	−0.066	0.781	1.283	0.047
27	Electronics parts and components	0.013	0.055	0.006	0.804	0.323	0.275
28	Electrical equipment	0.025	−0.134	0.214	1.233	0.894	0.993
29	Transportation equipment	−0.006	0.065	−0.079	1.094	0.934	0.016
30	Precision machinery	−0.012	0.114	−0.057	1.116	0.826	0.010
31	Miscellaneous industrial products	−0.004	−0.349	0.229	0.990	1.016	0.974
Mean		−0.005	0.006	0.003	1.597	0.670	

Column (1) shows the contribution of the simple mean of MFPΔ. Columns (2) and (3) show the contribution of the cross-sectional correlation between MFPΔ and job creation share and job destruction share, respectively. All of the figures in columns one through three are simple means for those two-digit industry level statistics across time. Column (4) shows the fractions of the weighted average MFPΔ of jobs created represented by the covariance term. Column (5) shows the fractions of the weighted average MFPΔ of jobs destructed represented by the covariance term. The p values in column (6) are results from t tests on the null hypothesis that the mean of the weighted average MFPΔ of jobs created and that of jobs destructed are equal against the alternative hypothesis that the mean of the weighted average MFPΔ of jobs created is greater than the mean of the weighted average MFPΔ of jobs destructed

shocks will overstate the role of productivity heterogeneity in the distribution of jobs created (destructed) across plants.

6.2 Testing for the cleansing effects of recessions

This subsection explores the cyclical property of the efficiency of the restructuring process.[14] We use the growth rate of per capita real GDP as an indicator for the state of the aggregate economy and the growth rate of industry real output as an indicator of the industry-level economic condition. Bartelsman et al. (2009) argue for employing the covariance term in the Olley–Pakes decomposition formula, which is the difference between unweighted and weighted average productivities, as a measure of allocative efficiency comparable across industries or countries, because measurement problems affecting the levels of productivities are differenced out. Olley and Pakes (1996), Eslava et al. (2004) and Bartelsman et al. (2009) regress the Olley–Pakes covariance term against indicators of policy reform to shed light on the effect of reforms on resource allocation efficiency.

Our estimated equation is specified as follows:

$$Z_{jt} = \alpha + \beta g_t^{gdp} + \gamma g_{jt}^{y} + \sum_{i=1}^{8} \delta_i t_i + \sum_{k=1}^{22} \phi_k ind_k + \varepsilon_{jt}, \quad (6-1)$$

where Z_{jt} represents the Olley–Pakes covariance term for industry j in year t, g_t^{gdp} denotes per capita real GDP growth

[14] See Sect. 2.2 for a brief review of the theoretic debate on the effects of downturns on the effectiveness of the restructuring process.

Table 11 The cyclicality of the covariance between job creation share and firm-level efficiency measures

Dependent variable	$\mathrm{Cov}\left(\mathrm{TE}_{it}, s_{it}^{JC}\right)$	$\mathrm{Cov}\left(\mathrm{TE}\Delta_{it}, s_{it}^{JC}\right)$	$\mathrm{Cov}\left(\mathrm{T}\Delta_{it}, s_{it}^{JC}\right)$	$\mathrm{Cov}\left(\mathrm{SC}_{it}, s_{it}^{JC}\right)$	$\mathrm{Cov}\left(T\dot{F}P_{it}, s_{it}^{JC}\right)$	$\mathrm{Cov}\left(\mathrm{MFP}_{it}, s_{it}^{JC}\right)$	$\mathrm{Cov}\left(\mathrm{MFP}\Delta_{it}, s_{it}^{JC}\right)$
Industry real output growth	−0.009	−0.0007	0.003	0.023	0.025	−0.107	−0.018
	(0.016)	(0.0007)	(0.002)	(0.02)	(0.019)	(0.125)	(0.167)
Per capita real GDP growth	−0.28***	−0.009***	−0.048***	−0.332***	−0.389***	−0.068***	−0.017***
	(0.031)	(0.001)	(0.003)	(0.039)	(0.038)	(0.003)	(0.004)
R^2	0.467	0.741	0.888	0.627	0.663	0.534	0.424

All regressions include industry and year fixed effects (estimates not reported)

The regressions cover 207 industry-year observations. Heteroskedasticity-robust standard errors clustered by year are in parentheses

*** Significant at 1%

in year t, g_{jt}^{y} is industry j's growth rate of real output, t_is represent a set of year dummies, ind_ks are a set of 22 two-digit industry dummies, and ε_{jt} is a random disturbance with mean zero and a possibly non-constant variance.[15] Equation (6-1) is estimated by ordinary least squares (OLS). Since the variable of main interest, g_t^{gdp}, varies by year, then to account for heteroskedasticity we cluster the robust (Huber-White) standard errors by year. Recall that our data consist of 23 industries over 10 years. Since the first year of the sample is treated as pre-sampling, we are left with a balanced panel of 207 industry-year observations.

Table 11 reports the regression results for the covariance between a plant's performance and job creation share. Columns 1 through 7 respectively report the results when TE, TEΔ, TΔ, SC, $T\dot{F}P$, MFP and MFPΔ are used as the plant performance measure. No matter which plant performance measure is exploited, the coefficient on g_t^y is always insignificant, indicating that the efficiency of the job creation process is acyclical with respect to the industry's output growth.

Irrespective of the plant performance measure, the coefficient on g_t^{gdp} is always negative and significant at the 1% level. This finding provides the first evidence in the literature that the share of high performance plants in total job creation is countercyclical. In particular, our results indicate that an improvement in the macroeconomic environment is associated with an increase in the fraction of newly created jobs accounted for by plants that are less technically efficiency, are slower at enhancing their production technology and technical efficiency, and deviate from their optimal production scale. Increases in macroeconomic activities appear to scramble the performance ranking on which job creation decisions are based, rendering the creation process socially inefficient.

The estimated cyclicality of the correlation between job creation and plant performance is notably substantially lower when plant performance is measured by MFP and MFPΔ. A one percentage point decrease in g_t^{gdp} is predicted to raise $\mathrm{cov}\left(\mathrm{TE}_{it}, s_{it}^{JC}\right)$ by 0.0028, which is 18% of the mean of $\mathrm{cov}\left(\mathrm{TE}_{it}, s_{it}^{JC}\right)$.[16] However, a one percentage point decrease in g_t^{gdp} raises $\mathrm{cov}\left(\mathrm{MFP}_{it}, s_{it}^{JC}\right)$ $\left(\mathrm{cov}\left(\mathrm{MFP}\Delta_{it}, s_{it}^{JC}\right)\right)$ by 0.00068 (0.00017), which is only 0.32% (2.8%) of the mean of $\mathrm{cov}\left(\mathrm{MFP}_{it}, s_{it}^{JC}\right)$ $\left(\mathrm{cov}\left(\mathrm{MFP}\Delta_{it}, s_{it}^{JC}\right)\right)$. The foregoing may result from the fact that measure MFP is subject to impacts from idiosyncratic shocks irrelevant to g_t^{gdp}.

Table 12 exhibits the regression results for the covariance between a plant's performance and job destruction share. Regardless of the plant performance measure, the coefficient on g_t^y is always insignificant, implying that the share of jobs destructed accounted for by low performance plants is acyclical to the industry's output growth. An alternative way to state the result is that industry slowdowns have no cleansing effect.

Regarding the cleansing effect of aggregate economic downturns, we find that the coefficient of g_t^{gdp} is positive and significant at the 1% level in the equations for $\mathrm{cov}\left(\mathrm{T}\Delta_{it}, s_{it}^{JD}\right)$, $\mathrm{cov}\left(\mathrm{SC}_{it}, s_{it}^{JD}\right)$, $\mathrm{cov}\left(T\dot{F}P_{it}, s_{it}^{JD}\right)$, and $\mathrm{cov}\left(\mathrm{MFP}\Delta_{it}, s_{it}^{JD}\right)$. On the other hand, the coefficient of g_t^{gdp} is negative and significant at the 1% level in the equations for $\mathrm{cov}\left(\mathrm{TE}_{it}, s_{it}^{JD}\right)$ and $\mathrm{cov}\left(\mathrm{TE}\Delta_{it}, s_{it}^{JD}\right)$. Together, these results imply that a fall in real per capita GDP shifts jobs destructed towards high-TE and high-TEΔ plants whose technological change is sluggish and production scale adjustment is productivity-impeding.

The marginal effect of g_t^{gdp} on the covariance between job destruction share and plant performance is economically significant. For instance, a one percentage point

[15] Industry-level real output is calculated by the authors by summing up plant-level real output across plants in an industry.

[16] The mean, standard deviation, minimum, and maximum of real per capita GDP growth over the period 1992–2003 are 5.26, 2.68,–2.17, and 7.85%, respectively.

Table 12 The cyclicality of the covariance between job destruction share and firm-level efficiency measures

Dependent variable	$\mathrm{Cov}(\mathrm{TE}_{it}, s_{it}^{JD})$	$\mathrm{Cov}(\mathrm{TE}\Delta_{it}, s_{it}^{JD})$	$\mathrm{Cov}(\mathrm{T}\Delta_{it}, s_{it}^{JD})$	$\mathrm{Cov}(\mathrm{SC}_{it}, s_{it}^{JD})$	$\mathrm{Cov}(T\dot{F}P_{it}, s_{it}^{JD})$	$\mathrm{Cov}(\mathrm{MFP}_{it}, s_{it}^{JD})$	$\mathrm{Cov}(\mathrm{MFP}\Delta_{it}, s_{it}^{JD})$
Industry real output growth	−0.029	−0.0003	0.0006	0.028	0.029	0.13	0.191
	(0.033)	(0.0005)	(0.002)	(0.029)	(0.028)	(0.14)	(0.133)
Per capita real GDP growth	−0.277***	−0.021***	0.033***	1.684***	1.696***	0.003	0.041***
	(0.066)	(0.001)	(0.004)	(0.057)	(0.055)	(0.003)	(0.003)
R^2	0.573	0.815	0.865	0.694	0.689	0.621	0.412

All regressions include industry and year fixed effects (estimates not reported)

The regressions cover 207 industry-year observations. Heteroskedasticity-robust standard errors clustered by year are in parentheses

*** Significant at 1%

decrease in g_t^{gdp} is predicted to reduce $\mathrm{cov}(\mathrm{T}\Delta_{it}, s_{it}^{JD})$ by 0.00033, which is 33% of the mean of $\mathrm{cov}(\mathrm{T}\Delta_{it}, s_{it}^{JD})$. The same decrease in g_t^{gdp} dampens $\mathrm{cov}(\mathrm{SC}_{it}, s_{it}^{JD})$ by 0.01684, which is 24.4% of the mean of $\mathrm{cov}(\mathrm{SC}_{it}, s_{it}^{JD})$. It is worth noting that the estimated responses of $\mathrm{cov}(\mathrm{MFP}_{it}, s_{it}^{JD})$ and $\mathrm{cov}(\mathrm{MFP}\Delta_{it}, s_{it}^{JD})$ to changes in g_t^{gdp} are relatively modest. A one percentage point decrease in g_t^{gdp} reduces $\mathrm{cov}(\mathrm{MFP}\Delta_{it}, s_{it}^{JD})$ by 0.00041, which is only 11.7% of the mean of $\mathrm{cov}(\mathrm{MFP}\Delta_{it}, s_{it}^{JD})$.

In summary, our results indicate that both job creation and destruction are more based on the rate of technological change during periods of low GDP growth. Namely, creative destruction is more pronounced during economic contractions. Jobs destructed (created) during macroeconomic slowdowns are mainly from plants whose technological progress is stagnant (rapid). This countercyclical job reallocation efficiency may be caused by the fact that financial markets are more selective with respect to firms' technological innovation capability during economic contractions. Identifying the reasons underlying the procyclicality of the scrambling of the TΔ ranking, on which job creation and destruction decisions are based is key to understanding aggregate productivity dynamics. This is an interesting possible avenue for future research.

7 Conclusions

This study represents a first attempt to separately examine the allocation of jobs created and destructed across plants in terms of plant-level technical efficiency, technical efficiency change, scale effect, and technical change. We find that the average rate of technical change of jobs created is statistically significantly higher than that of jobs destructed. By contrast, the average technical efficiency score and the average rate of technical efficiency change of jobs created are lower than those for the jobs destructed. Taken together, these results imply that managerial skills to minimize idle resources and unproductive activities play minor roles in surviving the market selection process. The reallocation process appears to channel resources towards plants that adopt new technologies rapidly. Evidence is also found that both job creation and destruction are more based on the rate of technical change when the state of the aggregate economy is bad, confirming Schumpeter's hypothesis that the quality of restructuring improves during economic downturns.

The comparison between results based on the SFA and those based on the deterministic index number approach shows that the latter method tends to overstate the role of productivity heterogeneity in resource reallocation. This can be evidenced by the fact that the index number approach is unable to isolate true productivity from idiosyncratic shocks.

Our analysis provides two policy implications. First, policy actions aiming to restore the efficiency of restructuring should be undertaken during economic booms, as opposed to recessions. Second, as jobs destructed are found to be disproportionately clustered at less technologically innovative plants, it may be possible to ameliorate job destruction by subsidizing R&D and technology acquisition.

Since recessionary pattern, industrial structure, and job creation and destruction costs all differ vastly across countries, our empirical results may not be directly transferable to other economies. Nevertheless, the methodology we propose to empirically investigate the technical efficiency and productivity distribution of jobs created and destructed represents a novel way for understanding aggregate productivity dynamics in other economies around the world.

The understanding of the efficiency of the reallocation process can be improved along many dimensions. It is hoped that similar studies conducted in the future, perhaps using data on countries at various stages of development, will provide further evidence on the role of technical efficiency and technical change in resource reallocation and the cyclical pattern of the creative destruction process. This paper remains silent on how the efficiency of job creation and destruction depends upon industry and country characteristics, such as factor intensity, the strictness of labor protection, and the level of financial development. To this end, a necessary first step would be to assemble a three-dimensional dataset on job reallocation efficiency, i.e., industry-level panel data on job creation and destruction efficiency for a wide sample of countries. We consider these to be fruitful avenues for future research.

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